MITIGATION STRATEGIES FOR CHALLENGES IN ADOPTION OF DATA SCIENCE IN INDUSTRY 4.0

by

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ABSTRACT

MITIGATION STRATEGIES FOR CHALLENGES IN ADOPTION OF DATA SCIENCE IN INDUSTRY 4.0

Manufacturing Industries are currently undergoing a digital transformation called Industry 4.0 (I 4.0) to face the challenges of the Volatile, Uncertain, Complex and Ambiguous (VUCA) world. I 4.0 makes factories smart with cyber physical systems, Internet of Things (IOT) and high-performance computing technologies. Industrial Internet of Things (IIOT) provides a lot of data on the performance of cyber physical systems. These data tell stories both good and bad about the condition of the product it produces, the process that is used for production and performance of the process as well as performance of the product when used by customer like Original Equipment Effectiveness, Specific energy consumption etc. With the advancement and availability of information, communication, and computing technologies these data can be processed to improve the production capacity, efficiency, and reliability. Without the wisdom of data science, I 4.0 would not be able to decode and bring out value from these data to understand and adapt the challenges the manufacturing industries are facing in this VUCA world. Data driven approaches are not new for Manufacturing Industries, for example Lean Six Sigma (LSS) has been in practice for a long time. Though it is not new, adaptation of data science in the digital transformation journey of a manufacturing industry is facing many challenges like change management, human / social management etc. This research focuses on identifying the challenges the manufacturing industry faces while adopting data science in the digital transformation journey and suggests mitigation strategies for those challenges. The finding of this research would support faster adaptation of data science in industry which is taking a new avatar through I4.0.

1. INTRODUCTION

The Fourth Industrial Revolution, also known as Industry 4.0, has brought about a significant shift in the way businesses operate. The integration of advanced technologies such as the Internet of Things (IoT), big data, and artificial intelligence (AI) is transforming the way organizations collect, process, and analyze data. However, the adoption of data science in Industry 4.0 also brings about several challenges that need to be addressed. This research work aims to explore the challenges faced in the adoption of data science in Industry 4.0 and the various mitigation strategies that have been proposed to address these challenges. Literatures suggests that by addressing these challenges and implementing effective mitigation strategies, organizations can better leverage the benefits of data science in Industry 4.0 to improve their operations and gain a competitive advantage (Gupta et al., 2020; Omar et al., 2019; Yin et al., 2020).

Data science can be used to optimize the production process of automobile parts manufacturing, by analyzing production data and identifying bottlenecks and inefficiencies (Dobra & Jósvai, 2021). Data science can be used to predict and prevent equipment failures in automobile parts manufacturing plants, which can lead to significant savings in maintenance costs and improve the overall efficiency of operations (Çınar et al., 2020). Data science can also be used to optimize the quality of automobile parts, by analyzing data from quality control tests and identifying patterns in product defects (Aichouni et al., 2021; Yadav et al., 2021). The automobile parts manufacturing industry is facing challenges in terms of data collection and management, as many processes are still manual, and data is often unstructured. Mitigation strategies proposed to address the challenge of data collection and management in the automobile parts manufacturing industry include the implementation of Industry 4.0 technologies such as IoT and smart sensors to improve data collection, and the use of data visualization tools to analyze data (Peres et al., 2020).

Below are the challenges in the adoption of data science in Industry 4.0

1. Lack of skilled workforce: There is a shortage of data scientists and other professionals with the skills necessary to implement and utilize data science in Industry 4.0.

2. Data quality and availability: Industry 4.0 environments generate vast amounts of data, but it is not always of high quality or easily accessible.
3. Integration with existing systems: Data science solutions must be integrated with existing systems and processes, which can be a complex and time-consuming task.
4. Privacy and security concerns: As Industry 4.0 environments generate vast amounts of data, privacy and security become a concern.
5. Scalability: Data science solutions must be able to handle large amounts of data and scale as necessary to meet the demands of Industry 4.0 environments.
6. Alignment with business objectives: Data science solutions must be aligned with the overall business objectives to be effective.
7. Lack of standardization: There is a lack of standardization in data science methodologies, tools, and technologies, making it difficult for organizations to adopt and implement data science solutions.

Though these challenges are generalized, it requires different mitigation strategies to be applied for different functions in a typical organization value chain. This research attempts to provide mitigation strategies for major functions in a typical organization starting from research and development, marketing, sales, manufacturing, and after-market support. Thus, the research work can be used as a playbook for the implementation of digital transformation projects in a typical Industry, which is important for industry practice / knowledge advancement.

1.1 Problem Statement

The importance of adoption of data science in the digital transformation projects while embracing the industry 4.0 or 5.0 journey by organizations has long been recognized by the industry. However, numerous digital transformation projects with data science elements are still plagued by delays and cost overruns or return of investment dilemma, which can frequently be traced to ineffective identification and treatment of challenges associated with it. First, when the challenges are not properly identified during project planning and subsequent conflicts in the execution phase of the projects are inevitable.

Digital transformation projects with data science features are becoming more and more technically complex due to various challenges and economically challenging, which exposes organization’s to even more complex constraints. Second, applying the traditional project management methods used by organizations for data science related projects is adding more complexity.

1.2 Research Questions

Below research questions are investigated in this work

1. What are the typical challenges in the adoption of data science in Industry 4.0 / 5.0 projects?

2. How to mitigate these challenges when orchestrating digital transformation projects as part of Industry 4.0 / 5.0 projects with data science features?

3. How can these mitigation strategies be deployed for various functions in a typical organization?

1.3 Research Objectives

The long-term goal of the research is to develop a formalized constraint management system. Constraint management is defined herein as the process of identifying, classifying, modeling, and resolving constraints. The objective of the current study is to provide a comprehensive review of literature and industry practices in relation to constraint analysis and outline a conceptual framework for constraint management. Particularly, the study has the following sub-objectives:

1. To provide a comprehensive review of challenges in implementing digital transformation projects with data science features

2. To propose mitigation strategy for the identified challenges

3. To review current industry practices and research in this area

The result of this study will be valuable to the industry practitioners as well as related service and software providers in developing better practice and tools which can address the different challenges that arise while implementing digital transformation projects with data science feature.

2. LITERATURE REVIEW

A preliminary literature review shows that there are many challenges a manufacturing industry is facing like quality, productivity, profitability, and sustainability(Khan et al., 2023; Omar et al., 2019). These challenges are widely mitigated by industry managers by using practices like Lean Six Sigma methodologies (LSS), Total Productive Maintenance (TPM), Toyota Production System (TPS), World Class Manufacturing (WCM) etc., (Fahle et al., 2020). Literatures also support those conventional methods like LSS, TPM, TPS etc., complements the adoption of Industry 4.0 (I 4.0) (Yadav et al., 2021). Lean 4.0, a conjunction of I 4.0 and Lean manufacturing, is widely discussed in literature as a current state of the art. Studies focusing on how implementation of I4.0 can be speeded up, throws a negative insight against Lean 4.0 (Bhat et al., 2021; Yadav et al., 2021). It is also clear with the literatures that with adoption of IIOT as part of I 4.0 transformation journey, vast amount of data is being collected but processing those data for the business objective is still a challenge (Jayaram, 2016). Positive association of Data driven Six Sigma methodology for speeding up I 4.0 adoption is also evident in some of the literature. Processing the data collected from these IIOT infrastructures is not happening at the scale that is expected. The need for analytical tools for processing these data are also recommended. Many literatures discuss on using data analytics for digital transformation are evident. The following sections review the different challenges discussed in the past chapters and high-level mitigation strategies for those challenges proposed by different literature.

2.1 Challenges – Lack of skilled workforce

One of the main challenges in the adoption of data science in Industry 4.0 is the lack of data science talent and skills. According to (Priestley & McGrath, 2021), there is a shortage of data scientists and analytics professionals in the market, making it difficult for organizations to find the right talent to implement data science projects. Additionally, the study found that there is a lack of training and development programs to equip employees with the necessary skills to work with data science tools and technologies. Several studies have highlighted the lack of data science talent and skills as a major challenge in the adoption of data science in Industry 4.0 (Alireza et al., 2022; Priestley et al., 2021). Many organizations struggle to leverage the full potential of data science due to a lack of understanding of the capabilities and limitations of data science technologies. Organizational culture and mindset can also be a significant obstacle to the adoption of data science in Industry 4.0. Employees may be resistant to change, and organizations need to develop strategies to overcome this resistance (Rana & Rathore, 2023). The ability to communicate and interpret data insights is also a critical challenge in the adoption of data science in Industry 4.0 (Mikalef & Krogstie, 2019).

2.2 Mitigation – Lack of skilled workforce

Mitigation strategies proposed to address the challenge of lack of data science talent and skills include investing in training and development programs for employees, hiring data science consultants, and outsourcing data science projects to specialized firms. One proposed mitigation strategy for the lack of data science talent and skills is to invest in training and development programs for employees. This includes providing employees with access to online training and certification programs, as well as on-the-job training opportunities. Additionally, organizations can also consider hiring data science consultants or outsourcing data science projects to specialized firms (Alireza et al., 2022). To address the challenge of lack of understanding of data science capabilities and limitations, organizations can invest in data science education and training programs for employees (Li, 2022). Organizations need to ensure that data scientists and non-technical employees have the necessary skills to communicate and understand data insights (Mikalef & Krogstie, 2019). Organizations need to consider the impact of data science in Industry 4.0 on employees, including the potential for job displacement and the need for reskilling and upskilling (Alireza et al., 2022; DeMasi et al., 2020).

2.3 Challenges - Integration with existing systems

Data governance and regulatory compliance are also major challenges in the adoption of data science in Industry 4.0, as organizations struggle to implement effective data governance processes and often lack the necessary resources and expertise to do so

(Abdellaoui et al., 2019; Fahle et al., 2020). One of the main challenges in the adoption of data science in Industry 4.0 is the lack of integration with existing systems and processes (Li et al., 2021). Another challenge is the lack of data governance and regulatory compliance. As organizations collect and process large amounts of data, it is important to ensure that the data is protected and used in compliance with regulatory requirements (Cao, 2017). However, many organizations struggle to implement effective data governance processes and often lack the necessary resources and expertise to do so.

Many industries are facing challenges in terms of data integration and management, due to the large number of legacy systems and manual processes in their automobile manufacturing operations (Cao & Iansiti, 2022). Critical industries such as oil and gas are facing these challenges as the cost of retrofit is also very high and integration of modern systems with AI capability with the traditional systems leads to slow down in adoption of data science (Olaizola et al., 2022). Connecting information systems from different hierarchical levels in a typical industrial setup to support faster decision making by intelligent algorithms requires upgradation of the existing system to provide real-time data flow (Tabim et al., 2021).

2.4 Mitigation – Integration with existing systems

To address the challenge of data governance and regulatory compliance, organizations can implement data governance frameworks and best practices, invest in data governance software and tools, and appoint a data governance team to oversee compliance processes(Marco & Satya, 2022). Mitigation strategies proposed to address the ethical and legal implications of data science in Industry 4.0 include the development of data privacy and security best practices and the appointment of a data ethics committee with data stewards (Marco & Satya, 2022).

The role of data science in Industry 4.0 is to empower organizations to make data-driven decisions, organizations need to ensure that data insights are actionable and can be used to drive business outcomes (Cao, 2017). Organizations need to consider the ethical and legal implications of data science in Industry 4.0, such as data privacy and data protection laws (Dyatkin, 2022).

The successful adoption of data science in Industry 4.0 requires a cross-functional approach, organizations need to involve different departments and teams to ensure data science projects align with business goals and objectives (Vafaeenezhad & Tavakkoli-Moghaddam, 2016). To address the challenge of data governance and regulatory compliance, organizations can implement data governance frameworks and best practices (Yin et al., 2020). This includes establishing clear policies and procedures for data collection, storage, and usage, as well as appointing a data governance team to oversee the implementation of these policies. Additionally, organizations can also invest in data governance software and tools to automate compliance processes (Črešnar et al., 2020).

2.5 Challenges – Infrastructure and Scalability

Another challenge in the adoption of data science in Industry 4.0 is the lack of standardization and interoperability of data science tools and technologies (Marco & Satya, 2022). One of the challenges of data science in Industry 4.0 is the complexity of data, organizations need to implement sophisticated data management and processing tools to handle large amounts of data and extract insights from it (Fahle et al., 2020). Organizations need to consider the scalability and sustainability of data science projects in Industry 4.0, as the volume of data is expected to grow exponentially in the future (Barletta et al., 2021).

Glass Manufacturing industries have implemented data science techniques to optimize their glass production process, resulting in significant improvements in energy efficiency and product quality. Glass Manufacturing industries has also used data science to improve their supply chain management, by analyzing data on customer demand and inventory levels to optimize production and logistics (Benoît, 2022). Glass Manufacturing industries have implemented Industry 4.0 technologies such as IoT and smart sensors to improve data collection and monitoring of their glass manufacturing plants, allowing for real-time adjustments to production processes. Glass Manufacturing industries has faced challenges in terms of data integration and management, due to the large number of legacy systems and manual processes in their glass manufacturing operations (Brecher et al., 2021). Glass

Industry has implemented data science techniques to optimize their glass production process, resulting in significant improvements in energy efficiency and product quality. Glass Industry has used data science to improve their supply chain management, by analyzing data on customer demand and inventory levels to optimize production and logistics (Lampathaki et al., 2021). Glass Industry has implemented Industry 4.0 technologies such as IoT and smart sensors to improve data collection and monitoring of their glass manufacturing plants, allowing for real-time adjustments to production processes. Glass industry has faced challenges in terms of data integration and management, due to the large number of legacy systems and manual processes in their glass manufacturing operations (Ameli et al., 2022).

2.6 Mitigation – Infrastructure and Scalability

Several studies have also discussed the importance of investing in data science infrastructure and technologies to enable the effective adoption of data science in Industry 4.0. Organizations need to consider the integration of data science with other Industry 4.0 technologies such as Industrial internet of things, manufacturing execution suite, enterprise resource planning software, product engineering tools, digital marketing and robotic process automation to fully leverage the benefits of data science in Industry 4.0 (Marco & Satya, 2022). Mitigation strategies proposed to address the challenge of lack of integration with existing systems and processes include investing in data integration tools and technologies and developing data integration best practices (Tabim et al., 2021). Mitigation strategies proposed to address the challenge of lack of standardization and interoperability include the development of data science standards and the adoption of open-source data science tools (Antonino et al., 2022). Mitigation strategies proposed to address the challenge of data collection and management in the manufacturing industry include the implementation of data collection systems and the use of data visualization tools to analyze data (Arruda et al., 2023). Mitigation strategies proposed by literatures to address the challenge of data integration and management include the implementation of data governance frameworks and the use of data visualization tools to analyze data (Bettinelli et al., 2020; Reslan et al., 2021; Schulze et al., 2020; Yin et al., 2020).

2.7 Challenge – Privacy and security concerns

Data security is a major concern in the adoption of data science in Industry 4.0 which includes cybersecurity risk, risk due to the vulnerability that arose due to legacy system, data breach due the cyber security risk, insider threat due the access of data in a single data warehouse infrastructure. With increased connectivity and data exchange, manufacturing systems become more vulnerable to cyber-attacks. Data science applications are susceptible to hacking, malware, ransomware, and other cyber threats that can disrupt operations and compromise sensitive data (Jakobsson et al., 2023; Voronov et al., 2023).

Legacy Systems Integration: Integrating data science technologies into existing legacy systems may expose security vulnerabilities if not properly managed. Older systems may lack robust security features, making them susceptible to attacks (Cao & Iansiti, 2022).
Promptly detecting data breaches and responding effectively is crucial. Data science can be instrumental in developing predictive models for identifying suspicious activities and streamlining incident response processes (Brecher et al., 2021; Khan et al., 2023). The manufacturing industry often relies on a large workforce, which can create potential insider threats. Employees or third-party vendors with access to critical data could misuse or intentionally leak information (Benoît, 2022).

2.8 Mitigation – Privacy and security concerns

Organizations need to ensure the protection of sensitive and confidential data from unauthorized access and breaches (Mabkhot et al., 2021). To address these challenges, manufacturing industries must implement robust cybersecurity measures, educate employees about data security best practices, and regularly update and monitor security protocols. A comprehensive security strategy should involve a combination of technology, policy, and employee awareness to protect sensitive data and maintain the trust of stakeholders(Carbone et al., 2016; Khan et al., 2023). Many literature suggests that organizations need to be aware of the ethical and legal implications of data science in Industry 4.0, particularly in regard to data privacy and security(Atzeni et al., 2023).

2.9 Challenges – Data quality and availability

Data governance and data quality management are important factors for the successful adoption of data science in Industry 4.0. Organizations need to implement data governance frameworks and best practices to ensure data integrity and compliance with regulations (Marco et al., 2022). Data science can be used to optimize the production process of manufacturing, by analyzing production data and identifying bottlenecks and inefficiencies (Khan et al., 2023). Data science can be used to predict and prevent equipment failures in manufacturing plants, which can lead to significant savings in maintenance costs and improve the overall efficiency of manufacturing operations. Data science can also be used to optimize the quality of glass products, by analyzing data from quality control tests and identifying patterns in product defects (Lampathaki et al., 2021). The manufacturing industry is facing challenges in terms of data collection and management, as manufacturing plants often have a large number of manual processes and data is often unstructured (Abdellaoui et al., 2019). Data quality and data integrity are also major challenges in the adoption of data science in Industry 4.0, as organizations often struggle to ensure the accuracy and completeness of their data (Tabim et al., 2021).

Data science can be used to optimize the performance of solar panels and improve the efficiency of energy production (Peña et al., 2022). Data science can be used to predict and prevent equipment failures in power plants, which can lead to significant savings in maintenance costs and improve the overall efficiency of operations (Kam et al., 2021). Data science can also be used to optimize the placement and alignment of solar panels, by analyzing solar patterns and predicting the most efficient locations for solar panel placement. The solar industry is facing challenges in terms of data collection and management, as solar panels are often located in remote areas and the data they generate is often of low quality (Khan et al., 2023).

Data science can play a crucial role in the wind turbine industry, by optimizing the performance of wind turbines and reducing the costs of energy production (Khan et al., 2023; Yucesan et al., 2023; Zhao et al., 2022). Data science can be used to predict and prevent equipment failures in wind turbines, which can lead to significant savings in maintenance costs and improve the overall efficiency of wind turbine operations (Yucesan et al., 2023). Data science can also be used to optimize the placement and alignment of wind turbines, by analyzing wind patterns and predicting the most efficient locations for wind turbine placement. The wind turbine industry is facing challenges in terms of data collection and management, as wind turbines are often located in remote areas and the data they generate is often of low quality (Zhao et al., 2022).

2.10 Mitigation – Data quality and availability

Mitigation strategies proposed by literatures to address the challenge of data integration and management include the implementation of data governance frameworks and the use of data visualization tools to analyze data (Arruda et al., 2023; Črešnar et al., 2020). Mitigation strategies proposed to address the challenge of data collection and management which includes data quality problem in the glass manufacturing industry include the standardization of data collection systems and the use of data visualization tools with extract load and transform features to analyze the data (Marco et al., 2022). Mitigation strategies proposed to address the challenge of data collection and management in the solar and wind industry include the use of IoT devices to improve data collection and the implementation of data management best practices (Khan et al., 2023). Mitigation strategies proposed to address the challenge of data collection and management in the manufacturing industry include the implementation of Industry 4.0 technologies such as IoT and smart sensors to improve data collection, and the use of data visualization tools to analyze data (Peres et al., 2020).

Data quality and data integrity can be improved through the implementation of data quality assessment tools (Luckin, 2017). Data quality and data integrity can be improved through the implementation of data quality management best practices and the use of data quality assessment tools. Organizations need to have a clear data strategy in place to ensure that data is being collected, processed, and analyzed in a way that aligns with their business goals and objectives (Gopal et al., 2019) .

2.11 Challenge Lack of standardization

Standardization is a significant challenge when it comes to adopting data science in the context of Industry 4.0 or digitalization. Some of the main challenges include:

1. Lack of agreed-upon standards: There is currently a lack of consensus on what standards should be used in data science, making it difficult for organizations to adopt and implement data science solutions. (Peres et al., 2020).

2. Complexity of Industry 4.0 environments: Industry 4.0 environments are highly complex, involving many different technologies and systems, which can make standardization difficult (Yin et al., 2020).

3. Lack of standardization in data science methodologies: There is a lack of standardization in data science methodologies, which makes it difficult for organizations to adopt and implement data science solutions (Goebel et al., 2021).

4. Difficulty in integrating data science solutions with existing systems: Data science solutions must be integrated with existing systems and processes, which can be a complex and time-consuming task (Khan et al., 2023; Tabim et al., 2021).

5. Privacy and security concerns: Industry 4.0 environments generate vast amounts of data, making privacy and security a concern (Jakobsson et al., 2023; Pandey et al., 2023).

6. Scalability: Data science solutions must be able to handle large amounts of data and scale as necessary to meet the demands of Industry 4.0 environments (Gupta et al., 2020).

7. Alignment with business objectives: Data science solutions must be aligned with the overall business objectives to be effective (Gupta et al., 2020; Yin et al., 2020).

8. Lack of collaboration and cooperation among various stakeholders: Data science solutions require collaboration and cooperation among various stakeholders such as

researchers, practitioners, and standardization bodies, which is often difficult to achieve (Alireza et al., 2022; Li et al., 2021).

These challenges can hinder the successful adoption and implementation of data science solutions in Industry 4.0 and digitalization. It is important to address these challenges to fully realize the potential benefits of data science in these environments.

2.12 Mitigation – lack of standardization

There are several strategies that have been proposed to mitigate the challenges associated with standardization in adopting data science in Industry 4.0 and digitalization. Some of these include:

1. Developing and adopting industry-wide standards: Developing and adopting industry-wide standards for data science methodologies, tools, and technologies can help to promote consistency and reduce complexity (Goebel et al., 2021; Yin et al., 2020).
2. Investing in education and training: Investing in education and training programs for current employees can help to develop the necessary skills for data science implementation in Industry 4.0 environments, so that standardization is possible with clear understanding among the interested parties and stake holders (Alireza et al., 2022; Li et al., 2021).
3. Investing in data integration and management tools: Investing in data integration and management tools can help to streamline the process of integrating data science solutions with existing systems (Abdellaoui et al., 2019; Tabim et al., 2021).
4. Adopting an API-first approach: Adopting an API-first approach can allow for easy integration of data science solutions with existing systems (Antonino et al., 2022).
5. Investing in data governance protocols: Implementing data governance protocols and processes can help to ensure the quality and integrity of data (Marco et al., 2022; Pandey et al., 2023).
6. Adopting data anonymization techniques: Adopting data anonymization techniques can protect the privacy of individuals as well as standardization of data science algorithms which can be generalized and deployed on different data sets whose meta data or header level information are standardized (Atzeni et al., 2023).

7. Using cloud-based solutions: Using cloud-based solutions can easily scale to meet the demands of Industry 4.0 environments where the infrastructure and it architecture are standardized (Caiza et al., 2020; Khan et al., 2023; Pandey et al., 2023).

8. Using technologies such as containerization and orchestration: Using technologies such as containerization and orchestration can help manage and scale data science solutions where standardization is a prerequisite and take in to account during designing the system (Caiza et al., 2020; Kubiak et al., 2022; Pandey et al., 2023).

9. Involving key stakeholders from different departments: Involving key stakeholders from different departments in the data science project can ensure alignment with overall business objective and in standardization of solutions with data science features (Bhat et al., 2021; Črešnar et al., 2020).

10. Regularly reviewing and assessing the performance of data science solutions: Regularly reviewing and assessing the performance of data science solutions can ensure they remain aligned with business objectives and abiding to the set standard (Arruda et al., 2023; Črešnar et al., 2020; Marco et al., 2022).

2.13 Conclusion

The adoption of data science in Industry 4.0 brings about several challenges, including the lack of data science talent and skills and the lack of data governance and regulatory compliance. However, several mitigation strategies have been proposed to address these challenges, including investing in training and development programs for employees and implementing data governance frameworks and best practices. By addressing these challenges at a micro level, organizations can better leverage the benefits of data science in Industry 4.0 to improve their operations and gain a competitive advantage. While existing scholarly articles address mitigation strategies for challenges in the adoption of data science, there remains a notable gap in research concerning its application across all major functions within the manufacturing sector. Specifically, there is a lack of micro-level understanding regarding the precise data science use cases required for each activity within the various sub-functions of manufacturing. This thesis aims to fill this gap by comprehensively outlining the different departments within a manufacturing industry and delving deeply into the specific functions within each department. By doing so, this research endeavors to provide a comprehensive outcome, serving as a playbook for every major function within the manufacturing industry.

3. METHODOLOGY

3.1 Overview of the Research Problem

The adoption of data science in Industry 4.0 and 5.0 projects presents various challenges for organizations undergoing digital transformation. These challenges arise due to the complexity of integrating data science features into existing manufacturing processes and value chains. Understanding these challenges and finding effective mitigation strategies is crucial for successful project orchestration.

3.2 Operationalization of Theoretical Constructs

The study aims to operationalize theoretical constructs by examining the challenges in the adoption of data science in Industry 4.0 and 5.0 projects, the strategies to mitigate these challenges, and the deployment of these strategies across various functions in a typical organization.

3.3 Research Purpose and Questions

The purpose of this research is to understand the challenges faced during the adoption of data science in Industry 4.0 and 5.0 projects and to identify and deploy effective mitigation strategies across various functions in a typical organization. The research addresses the following questions:

1. What are the typical challenges in the adoption of data science in Industry 4.0 / 5.0 projects?
2. How to mitigate these challenges when orchestrating digital transformation projects as part of Industry 4.0 / 5.0 projects with data science features?
3. How can these mitigation strategies be deployed for various functions in a typical organization?

3.4 Research Design

The research employs a systematic and comprehensive secondary research approach, focusing on a thorough analysis of existing literature covering various functional domains. This design involves examining scholarly articles, research papers, and other sources related to Industry 4.0 and 5.0 projects to identify challenges and potential strategies.

3.5 Population and Sample

The study covers a broad range of research papers and scholarly articles across 17 major functions, 150+ sub-functions, and 600+ activities within the manufacturing value chain. The research includes data from over 675 research papers, with approximately 3 to 4 scholarly articles per sub-function.

3.6 Participant Selection

Participant selection is not applicable, as the research relies on secondary sources such as scholarly articles and research papers from various databases. The focus is on existing literature rather than conducting new surveys or experiments.

3.7 Instrumentation

The primary instrument used in this research is the systematic and comprehensive analysis of existing literature related to Industry 4.0 and 5.0 projects, including challenges in data science adoption and potential mitigation strategies.

3.8 Data Collection Procedures

Data collection involves a review of secondary sources across the entire value chain of manufacturing, including product design, manufacturing planning, manufacturing engineering, and manufacturing execution. Articles and research papers were sourced from reputable academic journals and databases.

3.9 Data Analysis

Data analysis involves synthesizing information from the reviewed literature to identify common challenges and potential strategies in the adoption of data science within Industry 4.0 and 5.0 projects. The analysis aims to understand the application of these strategies across various functions in a typical organization.

3.10 Research Design Limitations

The primary limitation of this research design is its reliance on secondary sources, which may not capture the latest developments in the field. Additionally, there may be variability in the quality and scope of the reviewed sources, potentially impacting the comprehensiveness of the analysis.

3.11 Conclusion

This research methodology provides a comprehensive examination of the challenges in adopting data science in Industry 4.0 and 5.0 projects and explores strategies for mitigation. The analysis offers insights into how these strategies can be deployed across different functions in a typical organization. The findings contribute to a better understanding of the complexities of digital transformation projects and may guide future research and practical applications.

4. RECOMMENDED MITIGATION STRATEGIES FOR DATA SCIENCE ADOPTION CHALLENGES IN MANUFACTURING

This research aims to provide a wholistic view on adoption of data science across various major functions in a manufacturing organization covering product research and development in section 3.1, Manufacturing planning in section 3.2, Manufacturing engineering in section 3.3 and Manufacturing operations or execution in section 3.4. Under each main sections, there will be sub sections for different sub functions which will be detailing the basic activities carried out in those sub functions and scope for adopting data science. At Sub function level mitigation strategies for different challenges in adoption of data science are discussed.

Thus, this study delivers a comprehensive perspective on the adoption of data science throughout the key functions within a manufacturing organization. By delineating the application of data science across critical domains such as product research and development, manufacturing planning, engineering, and operations/execution, this research offers a detailed exploration of the potential benefits and challenges associated with integrating data science into each area. Through the examination of various sub-functions within these domains, including detailed analyses of their activities and the opportunities for data science implementation, this research work attempts to provide valuable insights for practitioners seeking to enhance their operations through data-driven approaches. Furthermore, by proposing mitigation strategies for the challenges inherent in data science adoption at the sub-function level, this research equips organizations with practical tools to navigate the complexities of implementing data science initiatives effectively. Ultimately, the research outcomes aim to empower manufacturing organizations to optimize their processes, improve decision-making, and drive innovation through the strategic deployment of data science methodologies.

4.1 Data Science in Product Design & Development and recommended mitigation strategies for challenges.

The dawn of Industry 4.0 represents a transformative era characterized by the integration of digital technologies into various facets of manufacturing. At the heart of this revolution lies the adoption and application of data science—a powerful toolset that promises unprecedented advancements in efficiency, innovation, and competitiveness. However, as industries strive to harness the potential of data science, they are confronted with multifaceted challenges, particularly within the realm of product design and development.

This chapter aims to dissect and address the intricate challenges faced by organizations in adopting data science within the function responsible for the design and development of products in the manufacturing industry. This pivotal function encompasses a spectrum of sub-functions ranging from Product Lifecycle Management (PLM) collaboration, quality, and governance to specialized areas like design simulation, systems engineering, and software application development. Each sub-function plays a distinct yet interconnected role in shaping product design, ensuring quality, and driving innovation.

As industries navigate the complexities of integrating data science into these sub-functions, they encounter a myriad of challenges. These may include technological barriers, such as data integration and interoperability issues; organizational challenges, such as skill gaps and cultural resistance to change; and strategic hurdles, such as aligning data science initiatives with overarching business objectives.

Against this backdrop, this chapter endeavors to elucidate the specific challenges impeding the seamless adoption of data science within each sub-function. By conducting a granular analysis, I aim to provide a comprehensive understanding of the root causes, implications, and repercussions of these challenges on product design and development processes.

Furthermore, recognizing that challenges often pave the way for innovation and improvement, this chapter delves into mitigation strategies tailored to address the identified hurdles. Drawing upon industry best practices, case studies, and academic research, I present actionable insights, frameworks, and methodologies designed to facilitate the effective integration of data science within the manufacturing sector's product design and development function.

In essence, this chapter attempts to navigate the complexities of Industry 4.0. By shedding light on the challenges and offering pragmatic mitigation strategies, I aspire to empower stakeholders—from industry leaders and decision-makers to data scientists and engineers—to harness the transformative potential of data science effectively. Through collaborative efforts, informed strategies, and relentless innovation, the manufacturing industry can unlock new horizons, driving sustainable growth, competitiveness, and excellence in the era of Industry 4.0 (Birkel et al., 2019; Frank et al., 2019; Ghobakhloo, 2018; Oztemel et al., 2020; Raj et al., 2020).

4.1.1 Mitigation Strategies for Challenges in Adoption of Data Science in product life cycle management collaboration, quality, and governance

Below would be the broad business processes in a typical function responsible for product life cycle management collaboration, quality, and governance.

- Program Management
- Standards, Global Attributes & Parameter Management
- Content and Document Management
- Change & Release Management
- Issue Management & CAPA
- Product & Portfolio Management
- Product Line Variability
- Intellectual Property Management
- Partner & Customer Collaboration
- Product Cost Management
- Advanced Product Quality Planning
- Failure Mode and Effects Analysis

- Audit Management
- Substance Compliance & Sustainability Management
- Environmental, Health & Safety (EHS)

In the following section, I will discuss in detail about each process and list down the different data science cases that can be orchestrated.

In today's rapidly evolving business landscape, managing a product's entire life cycle has become a complex yet pivotal task. A product's journey from ideation to retirement involves multifaceted processes that require meticulous oversight, collaboration, and governance. Central to this intricate dance are elements such as quality assurance, regulatory compliance, innovation, collaboration with stakeholders, and much more.

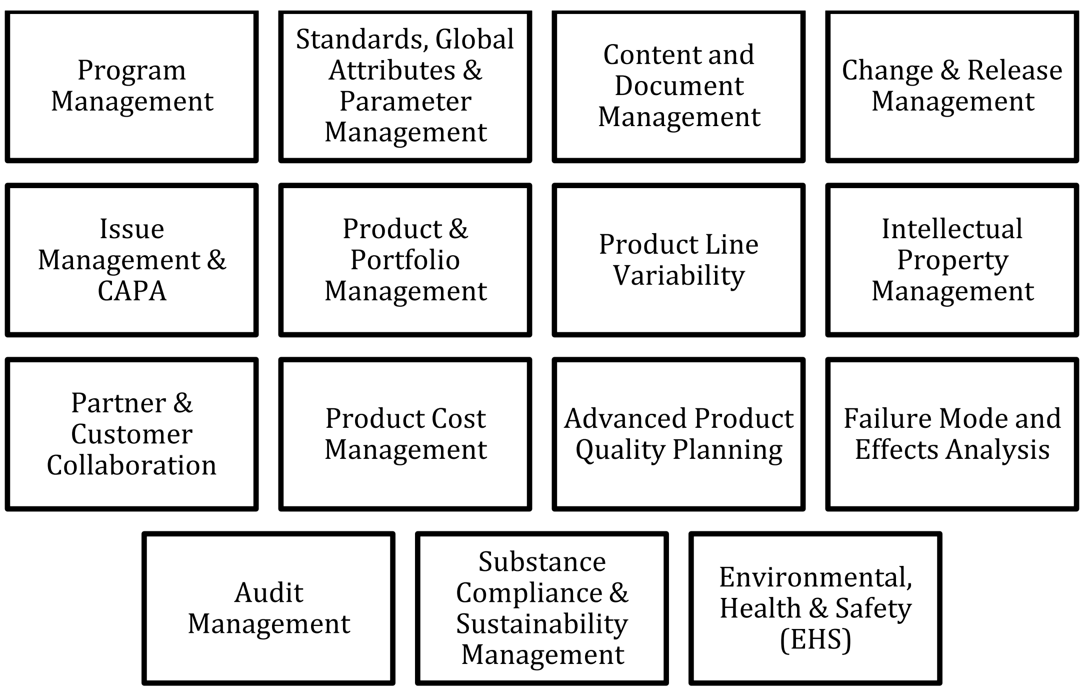

Figure 1 Typical Product Lifecycle Management Functions

Source: Author

This chapter delves deep into the various business processes integral to product life cycle management (PLM), focusing particularly on collaboration, quality, and governance aspects. Each process is a cog in the larger machinery of PLM, ensuring that products are developed, maintained, and eventually retired in an efficient, compliant, and sustainable manner.

From program management that oversees the holistic view of product development initiatives to standards and parameter management that sets the guidelines for quality and consistency, this chapter unravels the layers of complexities. It sheds light on content and document management, which ensures that critical information is stored, accessed, and updated seamlessly. Moreover, the chapter explores the mechanisms behind change and release management, addressing the need for agility while maintaining product integrity.

Quality remains at the forefront, with dedicated sections on advanced product quality planning, failure mode and effects analysis, and audit management. These processes aim to instill robust quality measures, anticipate potential risks, and ensure adherence to both internal standards and external regulations.

In an age where collaboration drives innovation, this chapter emphasizes the significance of partner and customer collaboration in shaping product development and enhancing market competitiveness. It also touches upon crucial facets like intellectual property management, product cost management, and substance compliance, underscoring their role in safeguarding assets, optimizing costs, and ensuring sustainability.

Furthermore, as businesses navigate the complexities of global markets and stringent regulations, the chapter sheds light on environmental, health, and safety considerations. It emphasizes the importance of adhering to sustainability norms, promoting eco-friendly practices, and prioritizing the well-being of stakeholders and the planet.

To add a contemporary touch, this chapter also introduces the intersection of data science with each PLM process. By identifying potential use cases, I explore how data-driven insights, analytics, and automation can revolutionize product life cycle management, driving efficiency, innovation, and strategic decision-making.

In essence, this chapter serves as a comprehensive guide, illuminating the critical processes, principles, and practices that underpin effective product life cycle management. By understanding these intricacies and embracing technological advancements, businesses can navigate challenges, seize opportunities, and deliver value consistently throughout a product's life cycle (Alshahrani, 2023; Bousdekis et al., 2023; Despeisse et al., 2020; Escobar et al., 2021; Lazarova-Molnar et al., 2019; Sajid et al., 2021).

4.1.1.1 Program Management

Program Management serves as a foundational pillar in orchestrating and overseeing multifaceted initiatives within an organization. It encompasses a series of interrelated sub-functions that are crucial for ensuring the successful execution, monitoring, and closure of programs.

Below are the detailed sub-functions integral to Program Management as show in figure *2*:

Define Program Targets and Initiate Program:
This initial phase involves setting clear objectives, defining scope, and initiating the program with the necessary resources, stakeholders, and governance structures in place.

Few data science use cases:

- Predictive Resource Allocation: Utilizing predictive analytics to forecast resource requirements based on historical data, project scope, and program objectives, ensuring optimal allocation of resources from the outset.
- Stakeholder Network Analysis: Conducting network analysis on stakeholder relationships and interactions to identify key influencers, potential bottlenecks, and communication channels, facilitating effective stakeholder engagement and alignment with program targets.

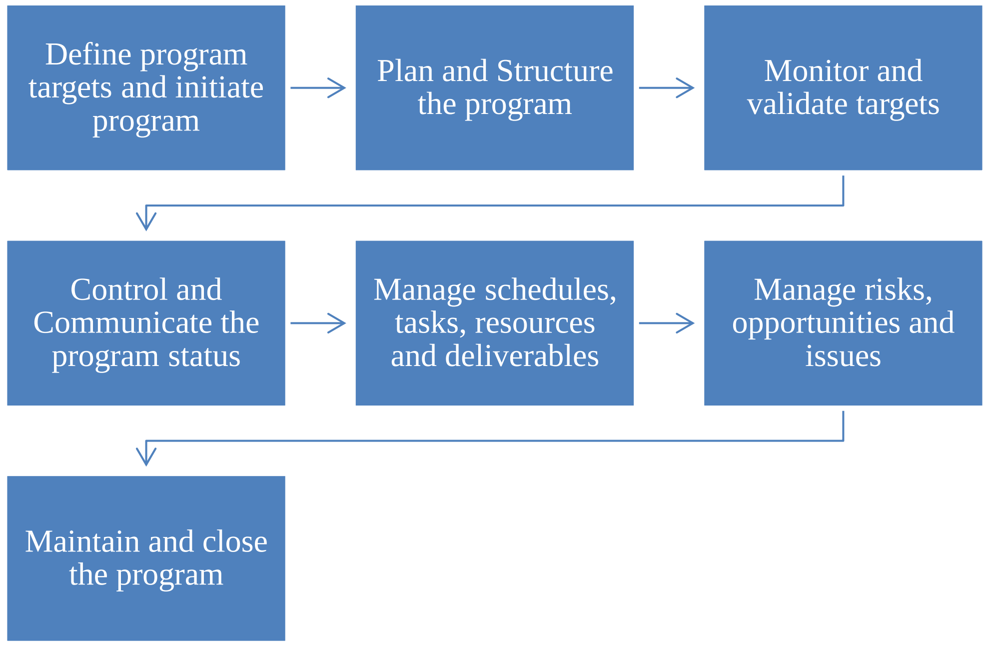

Figure 2 Program Management typical process flow. Source: Author

- Risk Assessment and Mitigation: Implementing data-driven risk assessment models to identify potential risks and uncertainties associated with the program's objectives and scope, enabling proactive mitigation strategies to minimize disruptions and delays.
- Automated Governance Framework: Developing machine learning algorithms to automate governance processes by monitoring compliance with program targets, identifying deviations, and triggering alerts or corrective actions as needed, ensuring adherence to established objectives and standards.

Plan and Structure the Program:

Here, the focus is on developing a comprehensive program plan, outlining milestones, timelines, and resource allocation to ensure alignment with organizational goals and objectives.

Few data science use cases:

- Resource Optimization: Utilizing predictive analytics to forecast resource needs throughout the program lifecycle. This involves analyzing historical data on resource usage, project requirements, and external factors to optimize resource allocation and scheduling, ensuring efficient utilization and cost-effectiveness.

- Risk Assessment and Mitigation: Applying machine learning algorithms to identify potential risks and their impact on the program's timeline and objectives. By analyzing historical data and identifying patterns, data science can help in assessing risk probability and severity, allowing program managers to proactively implement mitigation strategies.
- Stakeholder Analysis: Employing network analysis techniques to map out stakeholders involved in the program and their relationships. Data science can help identify key stakeholders, understand their influence, and predict potential conflicts or alignment issues, enabling effective stakeholder management and communication strategies.
- Performance Monitoring and Predictive Analytics: Implementing analytics dashboards to monitor program performance metrics in real-time. By analyzing performance data against predefined KPIs and benchmarks, data science can provide insights into program health, predict future performance trends, and facilitate data-driven decision-making to keep the program on track.

Monitor and Validate Targets:
Continuous monitoring and validation of program targets against predefined metrics and KPIs help in assessing progress and making necessary adjustments to stay on track.

Some data science use cases for Monitor and Validate Targets activity:

- Predictive Analytics for Target Achievement: Utilizing predictive analytics to forecast the likelihood of meeting program targets based on historical data and current trends, enabling proactive adjustments to strategies and resources.
- Anomaly Detection: Implementing anomaly detection algorithms to identify deviations from expected target trajectories, allowing for timely investigation and corrective actions.

- Performance Dashboard and Visualization: Developing interactive dashboards and visualizations that provide real-time insights into program performance relative to targets, facilitating data-driven decision-making and communication.
- Regression Analysis for Trend Identification: Conducting regression analysis to identify underlying trends and patterns in program metrics, supporting the identification of potential opportunities and risks.
- Optimization Algorithms for Resource Allocation: Applying optimization algorithms to allocate resources dynamically to different aspects of the program based on their impact on target achievement, maximizing efficiency and effectiveness.

Control and Communicate the Program Status:
Effective control mechanisms and transparent communication channels are vital for providing stakeholders with timely updates, addressing concerns, and ensuring alignment with organizational objectives. Few Data Science use cases are listed below.

- Dashboard Analytics**:** Implementing data-driven dashboards to visualize program metrics and key performance indicators, providing stakeholders with real-time insights into
- program status and performance.
- Predictive Analytics for Risk Management: Utilizing predictive analytics models to identify and prioritize potential risks to the program's success, enabling proactive risk mitigation strategies and decision-making.
- Natural Language Processing (NLP) for Stakeholder Sentiment Analysis: Applying NLP techniques to analyze stakeholder communications and feedback, allowing program managers to understand stakeholder sentiment and address concerns effectively.
- Machine Learning for Resource Allocation Optimization: Developing machine learning algorithms to optimize resource allocation across various program activities, ensuring efficient utilization of resources and timely completion of tasks.

- Time Series Analysis for Forecasting: Using time series analysis techniques to forecast future program milestones, schedules, and resource requirements, aiding in proactive planning and decision-making.

Manage Schedules, Tasks, Resources, and Deliverables:
Efficient management of schedules, tasks, resources, and deliverables ensures smooth execution, optimal resource utilization, and timely delivery of program outcomes.

Few Data Science Use Cases are listed below:

- Predictive Resource Allocation: Using predictive analytics to forecast resource requirements and allocate them optimally, ensuring efficient resource utilization and minimizing bottlenecks.
- Task Dependency Analysis: Employing graph-based algorithms to analyze task dependencies and optimize task scheduling for faster delivery of deliverables.
- Dynamic Task Prioritization: Implementing machine learning models to dynamically prioritize tasks based on factors like urgency, importance, and resource availability, enhancing overall schedule management.
- Delivery Time Estimation: Developing predictive models to estimate delivery times for different tasks or deliverables, aiding in setting realistic schedules and managing stakeholder expectations.
- Resource Capacity Planning: Utilizing data-driven approaches to plan resource capacities effectively, balancing workload distribution and avoiding resource shortages or overloads.

Manage Risks, Opportunities, and Issues:
Proactive identification, assessment, and mitigation of risks, while capitalizing on opportunities and addressing issues, are essential for safeguarding program integrity and maximizing value. Some data science use cases are listed below.

- Risk Prediction Models: Implement machine learning models to predict potential risks based on historical data and contextual factors, enabling proactive risk management.
- Opportunity Identification Algorithms: Develop algorithms to identify potential opportunities for improvement or innovation within the program, optimizing value delivery.
- Sentiment Analysis for Issue Detection: Utilize sentiment analysis techniques to detect and prioritize issues based on partner and customer feedback, facilitating timely resolution.
- Anomaly Detection: Employ anomaly detection algorithms to identify unusual patterns or deviations in program metrics, signaling potential risks or opportunities.
- Root Cause Analysis: Apply data-driven techniques to perform root cause analysis on past issues, enabling targeted mitigation strategies and preventing recurrence.
- Portfolio Risk Management: Utilize data science to assess and manage risks across the program portfolio, ensuring holistic risk mitigation strategies.
- Simulation and Scenario Analysis: Conduct simulation and scenario analysis using historical and projected data to assess the potential impact of different risk and opportunity scenarios on program outcomes.
- Predictive Analytics for Risk Trends: Implement predictive analytics to identify emerging risk trends and patterns, allowing for proactive mitigation actions.
- Resource Optimization Models: Develop optimization models to efficiently allocate resources across different program activities, minimizing exposure to risks while maximizing opportunities.
- Dynamic Risk Assessment Dashboards: Create interactive dashboards that provide real-time visibility into program risks, opportunities, and issues, enabling informed decision-making and timely intervention.

Maintain and Close the Program: Upon successful completion, the program is systematically closed, ensuring that all deliverables are met, lessons learned are documented, and value realization is achieved. Some data science use cases are listed below.

- Deliverable Completion Prediction: Predicting the likelihood of deliverables being completed on time using historical data and project progress metrics.
- Lessons Learned Mining: Applying natural language processing (NLP) techniques to extract insights and lessons learned from project documentation and communications.
- Value Realization Analytics: Analyzing project outcomes and performance metrics to measure and quantify the realized value of the program.
- Automated Closure Checklist: Developing algorithms to automate the generation and completion tracking of program closure checklists.
- Post-Implementation Analysis: Conducting data-driven analysis to assess the effectiveness and impact of program deliverables after implementation.

In summary, integrating data science into Program Management enhances agility, fosters collaboration, and drives value creation across the program lifecycle. By leveraging advanced analytics, artificial intelligence, and automation technologies, organizations can navigate complexities, capitalize on opportunities, and achieve strategic objectives effectively (Bomheuer et al., 2020; Choirat et al., 2019; Gupta et al., 2021; Heacock et al., 2022; Leyesa et al., 2020).

4.1.1.2 Change & Release Management

Below sections will discuss the various activities shown in *figure 3* and data science use cases applicable in these activities.

Design Change and Release Management is a critical component of Product Life Cycle Management (PLM) that focuses on efficiently managing modifications to product designs, ensuring compliance, and facilitating seamless implementation across the value chain.

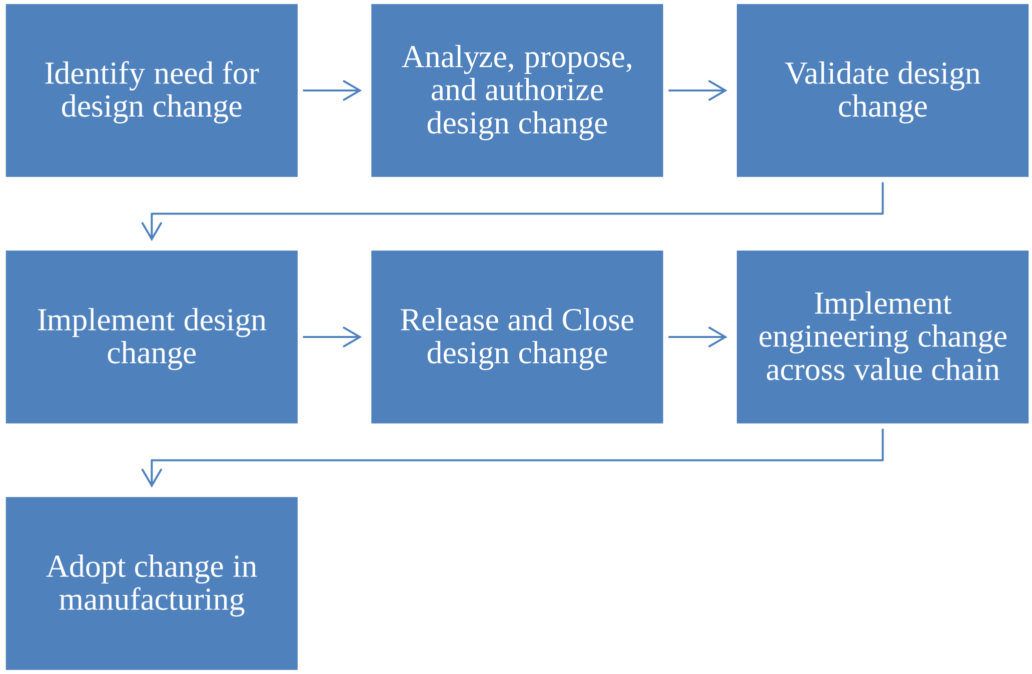

Figure 3 Typical Design Change and Release Management Process Flow.

Source: Author

This function encompasses several interrelated sub-functions, each playing a pivotal role in driving innovation, quality, and agility. Some data science use cases are listed below.

- Predictive Maintenance Models: Using machine learning to forecast equipment failures and schedule preventive maintenance, minimizing downtime and disruption during design changes.
- Anomaly Detection: Employing anomaly detection algorithms to identify unusual patterns in design change requests, flagging potential compliance issues or errors.
- Natural Language Processing (NLP) for Requirements Analysis: Applying NLP techniques to analyze and categorize customer requirements and feedback, guiding design change prioritization.
- Optimization Algorithms for Resource Allocation: Utilizing optimization algorithms to allocate resources efficiently during design changes, optimizing costs and timelines.

- Simulation and Modeling: Leveraging simulation and modeling techniques to predict the impact of design changes on product performance and quality, enabling informed decision-making.

Identify Need for Design Change:

The initial step involves recognizing and evaluating the need for design changes based on factors such as market feedback, performance metrics, regulatory requirements, and emerging technologies. Some data science use cases are listed below.

- Predictive Maintenance Models: Using data science to predict equipment failures and identify potential design changes to improve reliability and performance.
- Text Mining and Sentiment Analysis: Analyzing market feedback and customer reviews to identify patterns and sentiments that may indicate the need for design changes.
- Regression Analysis: Quantifying the impact of design parameters on performance metrics to identify areas for improvement.
- Anomaly Detection: Detecting deviations from expected performance or regulatory standards, signaling the need for design changes.
- Trend Analysis: Identifying emerging technologies or market trends that may necessitate design updates to stay competitive.

Analyze, Propose, and Authorize Design Change:

Here, cross-functional teams collaborate to analyze the impact, feasibility, and implications of proposed design changes. Upon evaluation, authorized stakeholders approve the modifications, ensuring alignment with strategic objectives and compliance standards. Some data science use cases are listed below.

- Predictive Modeling for Impact Assessment: Utilizing predictive modeling to forecast the potential impact of proposed design changes on product performance and quality.
- Optimization Algorithms for Feasibility Analysis: Applying optimization algorithms to assess the feasibility of proposed design changes considering constraints such as cost, resources, and time.

- Text Mining for Compliance Checking: Implementing text mining techniques to analyze design change documents and ensure compliance with regulatory standards and industry best practices.
- Decision Trees for Authorization Process: Utilizing decision tree algorithms to automate the authorization process for design changes based on predefined criteria and risk thresholds.
- Simulation and Modeling for Implication Evaluation: Using simulation and modeling techniques to simulate the effects of design changes on product behavior and evaluate potential implications before implementation.

Validate Design Change:

Validation processes, including prototyping, simulation, and testing, are conducted to validate the proposed design changes, ensuring they meet quality standards, performance criteria, and customer expectations. Some data science use cases are listed below.

- Simulation Optimization: Utilizing data science to optimize simulation parameters for faster and more accurate validation of design changes.
- Predictive Modeling for Failure Analysis: Developing predictive models to analyze potential failure modes and their likelihood, aiding in design change validation.
- Anomaly Detection in Testing Data: Applying anomaly detection techniques to testing data to identify unexpected behavior and validate design changes.
- Feature Importance Analysis: Conducting feature importance analysis to identify critical design parameters affecting performance and validate proposed changes accordingly.
- Model Calibration: Employing data-driven techniques to calibrate simulation models and ensure their accuracy in validating design changes.

Implement Design Change:

Once validated, the approved design changes are implemented across relevant stages of the product life cycle, ensuring seamless integration, minimal disruptions, and optimized resource utilization. Some data science use cases are listed below.

- Predictive Maintenance Models: Utilize machine learning to predict equipment failures, optimizing resource allocation during design change implementation.
- Simulation Modeling: Employ simulation techniques to assess the impact of design changes on the product life cycle, ensuring seamless integration.
- Optimization Algorithms: Implement optimization algorithms to optimize resource allocation and scheduling during design change implementation.
- Supply Chain Analytics: Apply data analytics to optimize the supply chain, ensuring timely availability of resources for design change implementation.
- Process Mining: Utilize process mining techniques to analyze and improve the efficiency of design change implementation processes.

Release and Close Design Change:

Upon successful implementation and validation, the design changes are formally released, documented, and closed, ensuring traceability, compliance, and value realization. Some data science use cases are listed below.

- Anomaly Detection: Using anomaly detection algorithms to identify any irregularities or unexpected outcomes during the release and closure process, ensuring quality and compliance.
- Predictive Analytics for Release Planning: Employing predictive analytics to forecast the optimal timing and resource allocation for releasing design changes, maximizing efficiency, and minimizing delays.
- Text Mining for Documentation: Utilizing text mining techniques to extract key information and insights from release documentation, facilitating traceability and knowledge management.
- Process Optimization: Applying process optimization algorithms to streamline the release and closure workflow, reducing cycle times, and improving overall efficiency.
- Compliance Monitoring: Implementing compliance monitoring systems that use data science techniques to ensure adherence to regulatory requirements and industry standards throughout the release process.

Implement Engineering Change Across Value Chain:

This involves coordinating with various stakeholders across the value chain, including suppliers, manufacturers, distributors, and service providers, to implement engineering changes efficiently and effectively. Some data science use cases are listed below.

- Supply Chain Optimization: Using data analytics to optimize the supply chain for efficient distribution and implementation of engineering changes.
- Predictive Maintenance: Employing predictive analytics to anticipate maintenance needs and minimize downtime during engineering change implementation.
- Demand Forecasting: Leveraging machine learning models to forecast demand and ensure the availability of resources during engineering change rollout.
- Network Optimization: Applying network optimization algorithms to optimize communication and collaboration among stakeholders in the value chain.
- Quality Control Monitoring: Implementing real-time monitoring systems to ensure quality control throughout the engineering change process.

Adopt Change in Manufacturing:

Manufacturing processes, systems, and workflows are updated to adopt the approved design changes, ensuring product quality, efficiency, and compliance throughout the production lifecycle. Some data science use cases are listed below.

- Predictive Maintenance: Using machine learning to predict equipment failures and schedule maintenance, minimizing downtime during the change adoption process.
- Quality Control Optimization: Implementing data analytics to optimize quality control processes and ensure adherence to quality standards during manufacturing changes.
- Process Automation: Leveraging AI and robotics to automate manufacturing processes and workflows, increasing efficiency and reducing human error during change adoption.
- Supply Chain Optimization: Applying data science techniques to optimize supply chain logistics and ensure timely delivery of materials for implementing design changes in manufacturing.

- Anomaly Detection: Utilizing anomaly detection algorithms to identify deviations from expected manufacturing outcomes, enabling rapid response and adjustment during change adoption.

In summary, integrating data science into Design Change and Release Management enhances agility, fosters collaboration, and drives innovation across the product life cycle. By leveraging advanced analytics, artificial intelligence, and automation technologies, organizations can navigate complexities, capitalize on opportunities, and achieve strategic objectives effectively (Chung, 2012; Klosterboer, 2008; Krishnan et al., 2022; Malhotra et al., 2018; Nwokeji et al., 2015).

4.1.1.3 Issue Management & Corrective Action and Preventive Action

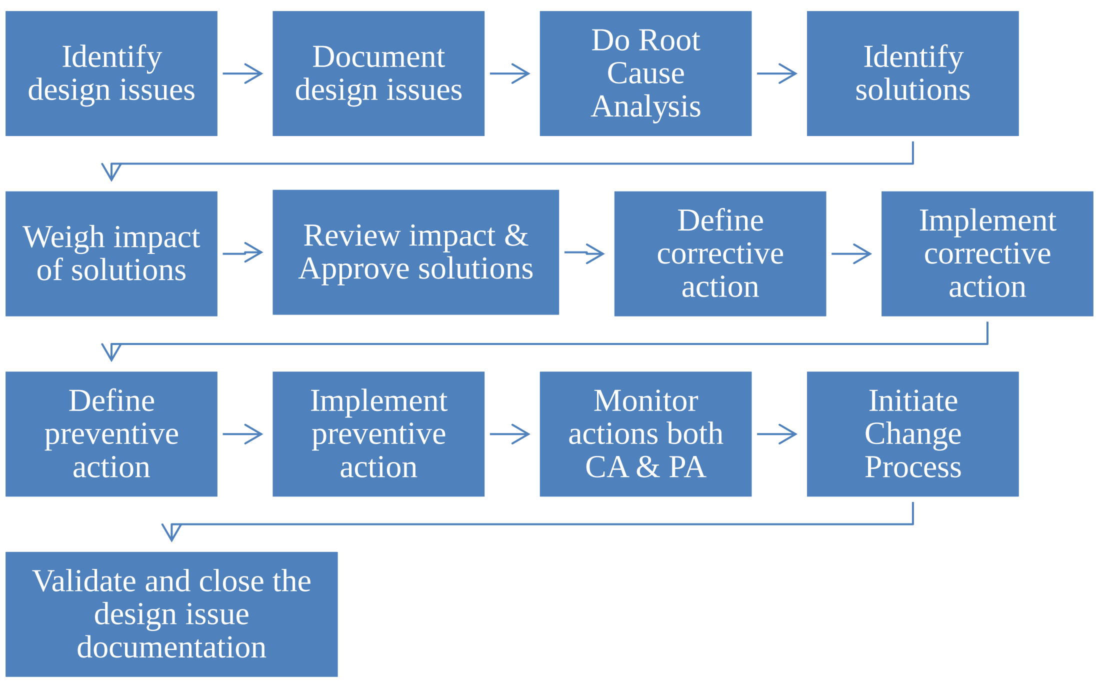

Figure 4 Typical Design issue management and CAPA process flow.

Source: Author

Issue Management & Corrective Action and Preventive Action (CAPA) are fundamental aspects of Product Life Cycle Management (PLM), ensuring that design flaws, process inefficiencies, and compliance deviations are systematically identified, analyzed, and addressed. This function plays a crucial role in enhancing product quality, operational efficiency, and regulatory compliance. Below sections will discuss about various activities shown in figure *4* and data science use cases applicable in these activities.

Identify Design Issues: The initial step involves detecting and documenting design issues through various channels such as customer feedback, quality inspections, testing, and monitoring systems. Some data science use cases are listed below.

- Anomaly Detection: Using anomaly detection algorithms to automatically flag deviations from expected design patterns in customer feedback and monitoring systems.
- Root Cause Analysis: Applying causal inference techniques to analyze quality inspection and testing data to pinpoint the root causes of design issues.
- Text Mining: Employing text mining and sentiment analysis to extract insights from customer feedback and identify recurring themes related to design problems.
- Failure Prediction Models: Developing machine learning models to predict potential design failures based on historical data from testing and monitoring systems.
- Quality Control Dashboard: Building interactive dashboards that visualize key design metrics and highlight areas of concern based on real-time data from quality inspections and testing processes.

Document Design Issues: Accurate and comprehensive documentation of design issues ensures traceability, accountability, and effective communication across stakeholders involved in the CAPA process. Some data science use cases are listed below.

- Text Mining for Issue Identification: Using text mining techniques to automatically identify and categorize design issues from documentation, streamlining the CAPA process.
- Anomaly Detection for Design Flaws: Implementing anomaly detection algorithms to identify unusual patterns or deviations in design documentation, flagging potential design flaws for further investigation.

- Knowledge Graphs for Relationship Mapping: Creating knowledge graphs to visualize relationships between different design issues, facilitating a better understanding of their interconnectedness and impact.
- Predictive Modeling for Risk Assessment: Developing predictive models to assess the risk associated with different design issues, prioritizing mitigation efforts for high-risk areas.
- Sentiment Analysis for Stakeholder Feedback: Employing sentiment analysis to gauge stakeholders' perceptions and reactions to design issues, informing communication strategies and decision-making in the CAPA process.

Do Root Cause Analysis: Root Cause Analysis (RCA) techniques, including Fishbone Diagrams, 5 Whys, and Fault Tree Analysis, are employed to identify underlying causes, contributing factors, and systemic issues leading to design flaws or process deviations. Some data science use cases are listed below.

- Anomaly Detection Models: Implement anomaly detection models to automatically identify unusual patterns or deviations in data, aiding in pinpointing potential root causes of anomalies.
- Causal Inference Techniques: Apply causal inference techniques to analyze relationships between variables and identify causal factors contributing to design flaws or process deviations.
- Text Mining for Incident Reports: Utilize text mining algorithms to analyze incident reports and extract key insights, facilitating the identification of root causes through qualitative data analysis.
- Simulation Modeling: Employ simulation modeling to simulate different scenarios and test hypotheses about potential root causes, providing insights into complex systems' behaviors.
- Predictive Maintenance Analytics: Leverage predictive maintenance analytics to anticipate equipment failures or malfunctions, enabling proactive identification of root causes and preventive actions.

Identify Solutions:

Based on RCA findings, cross-functional teams collaborate to brainstorm, evaluate, and identify viable solutions to address the identified issues effectively. Some data science use cases are listed below.

- Predictive Modeling: Using predictive modeling to anticipate future occurrences of identified issues, enabling proactive solution development.
- Anomaly Detection: Employing anomaly detection techniques to identify abnormal patterns or deviations in data, pinpointing potential root causes of problems.
- Decision Trees: Constructing decision trees to visualize potential cause-and-effect relationships among various factors contributing to the issues, aiding in solution prioritization.
- Simulation Modeling: Creating simulation models to test the effectiveness of different solution scenarios under various conditions, facilitating evidence-based decision-making.
- Text Mining: Applying text mining algorithms to analyze qualitative data such as customer feedback or incident reports, uncovering insights to inform solution development.

Weigh Impact of Solutions:

The potential impact, benefits, risks, costs, and feasibility of proposed solutions are evaluated to determine their efficacy and alignment with organizational objectives and stakeholder expectations. Some data science use cases are listed below.

- Predictive Analytics for Impact Assessment: Using predictive analytics to forecast the potential impact of proposed solutions, aiding in decision-making and risk management.
- Cost-Benefit Analysis Models: Developing cost-benefit analysis models that quantify the expected benefits and costs of proposed solutions, facilitating informed investment decisions.
- Risk Prediction and Mitigation: Applying data science techniques to identify and mitigate potential risks associated with proposed solutions, ensuring alignment with organizational objectives.

- Feasibility Assessment Algorithms: Implementing algorithms to assess the feasibility of proposed solutions based on technical, resource, and regulatory constraints, optimizing resource allocation.
- Stakeholder Sentiment Analysis: Conducting sentiment analysis on stakeholder feedback to gauge their perceptions and expectations regarding proposed solutions, ensuring alignment and buy-in.

Review Impact & Approve Solutions:

Authorized stakeholders review, assess, and approve the proposed solutions, ensuring alignment with quality standards, regulatory requirements, and strategic priorities. Some data science use cases are listed below.

- Predictive Analytics for Solution Impact: Utilizing predictive analytics to forecast the potential impact of proposed solutions on key metrics, aiding stakeholders in decision-making.
- Quality Control Monitoring: Implementing data-driven quality control measures to ensure proposed solutions meet predefined quality standards and regulatory requirements.
- Regulatory Compliance Analysis: Employing data science techniques to analyze proposed solutions for compliance with relevant regulations and standards.
- Stakeholder Sentiment Analysis: Using sentiment analysis to gauge stakeholder sentiment towards proposed solutions, facilitating more informed approval decisions.
- Strategic Alignment Assessment: Leveraging data analytics to assess the alignment of proposed solutions with strategic priorities, guiding stakeholders in prioritization and approval.

Define Corrective Action:

Clear and actionable corrective action plans are defined, outlining specific steps, responsibilities, timelines, and resources required to address and resolve the identified design issues. Some data science use cases are listed below.

- Root Cause Analysis: Using data analytics to identify underlying causes of design issues and inform corrective action plans.

- Predictive Modeling for Issue Identification: Developing models to predict potential design issues before they occur, enabling proactive corrective action.
- Optimization Algorithms for Resource Allocation: Applying optimization algorithms to allocate resources efficiently for implementing corrective actions.
- Natural Language Processing for Action Plan Generation: Utilizing NLP to automatically generate actionable corrective action plans based on identified design issues.
- Performance Monitoring and Feedback Analysis: Implementing systems to monitor the effectiveness of corrective actions and analyze feedback for continuous improvement.

Implement Corrective Action: The approved corrective action plans are executed diligently, ensuring timely implementation, monitoring progress, and verifying effectiveness through performance metrics and validation protocols.

Data Science Use Cases:

- Root Cause Analysis: Using data analytics to identify underlying causes of design issues, informing corrective action plans.
- Predictive Maintenance: Employing predictive models to anticipate potential design failures and proactively implement corrective actions.
- Anomaly Detection: Utilizing anomaly detection algorithms to flag deviations from expected design performance, triggering corrective actions.
- Optimization Algorithms: Applying optimization techniques to optimize corrective action plans for maximum efficiency and impact.
- Resource Allocation Optimization: Using data-driven approaches to allocate resources effectively within corrective action plans, ensuring timely resolution of design issues.

Define Preventive Action:

Proactive measures and preventive action plans are developed to mitigate recurrence, enhance system reliability, and prevent similar issues from arising in the future.

Data Science Use Cases:

- Anomaly Detection: Utilizing anomaly detection algorithms to identify early warning signs of potential issues or failures, enabling proactive intervention before they escalate.
- Root Cause Analysis: Applying data mining techniques to analyze historical data and identify underlying causes of past issues, informing preventive action plans.
- Predictive Maintenance: Implementing predictive maintenance models to forecast equipment failures and schedule maintenance activities before they occur, minimizing downtime and disruptions.
- Risk Prediction: Developing risk prediction models to anticipate future risks and vulnerabilities, allowing for proactive risk mitigation strategies.
- Continuous Monitoring: Setting up automated monitoring systems to continuously track system performance metrics and detect deviations from normal behavior, triggering preventive actions when necessary.

Implement Preventive Action:

The preventive action plans are implemented across relevant processes, systems, and functions, ensuring sustainability, continuous improvement, and adherence to best practices. Below are some data science use cases.

- Anomaly Detection: Utilize anomaly detection algorithms to identify deviations from normal processes or behaviors, enabling early intervention and preventive measures.
- Predictive Maintenance: Implement predictive maintenance models to anticipate potential failures in systems or equipment, allowing for proactive maintenance and prevention of downtime.
- Root Cause Analysis: Apply data-driven root cause analysis techniques to identify underlying factors contributing to issues or failures, informing targeted preventive actions.
- Quality Control Monitoring: Develop algorithms to monitor and analyze quality control data in real-time, enabling early detection of deviations and implementation of preventive measures.

- Continuous Monitoring and Feedback Loops: Establish continuous monitoring systems with feedback loops to evaluate the effectiveness of preventive actions and iteratively improve strategies over time.

Monitor Actions (Both CA & PA):

Continuous monitoring, tracking, and evaluation of corrective and preventive actions are conducted to assess progress, identify gaps, and make necessary adjustments based on real-time data and feedback. Below are some data science use cases for monitoring corrective and preventive actions:

- Anomaly Detection: Using anomaly detection algorithms to identify unexpected deviations in corrective and preventive action metrics, enabling timely intervention and adjustment.
- Root Cause Analysis: Employing data mining techniques to uncover underlying causes of issues and failures, informing targeted corrective actions for long-term prevention.
- Predictive Modeling: Developing predictive models to forecast the effectiveness of proposed corrective and preventive actions, guiding decision-making, and resource allocation.
- Text Mining for Feedback Analysis: Applying text mining and sentiment analysis to analyze feedback on corrective and preventive actions, extracting insights for continuous improvement.
- Dashboard Visualization: Creating interactive dashboards to visualize key performance indicators of corrective and preventive actions, facilitating real-time monitoring and decision-making.

Initiate Change Process:

Integrated change management processes are initiated to ensure seamless integration, alignment, and coordination of CAPA initiatives with broader organizational goals, initiatives, and regulatory requirements. Below are data science use cases for initiating change processes:

- Predictive Analytics for Change Impact: Using predictive analytics to forecast the potential impact of CAPA initiatives on organizational goals and regulatory compliance, aiding in strategic alignment.
- Natural Language Processing for Policy Analysis: Employing NLP to analyze and extract insights from regulatory documents and organizational policies, informing the design of CAPA initiatives.
- Network Analysis for Stakeholder Mapping: Utilizing network analysis to map stakeholders and their relationships within the organization, facilitating targeted communication and collaboration during change implementation.
- Process Mining for Workflow Optimization: Applying process mining techniques to analyze historical data and optimize change management workflows for efficiency and effectiveness.
- Simulation Modeling for Scenario Planning: Developing simulation models to simulate different scenarios of CAPA initiatives' implementation, enabling informed decision-making and risk mitigation strategies.

Validate and Close the Design Issue Documentation:
Upon successful implementation, validation, and verification of corrective and preventive actions, the design issue documentation is formally reviewed, approved, and closed, ensuring compliance, traceability, and value realization. Below are some data science use cases.

- Text Classification for Issue Prioritization: Utilizing text classification algorithms to prioritize design issues based on severity and impact, streamlining validation and closure processes.
- Anomaly Detection for Validation: Implementing anomaly detection techniques to identify unexpected patterns or discrepancies during validation, ensuring thorough verification of corrective actions.
- Workflow Optimization with Process Mining: Applying process mining techniques to analyze the validation and closure workflow, identifying bottlenecks and inefficiencies for optimization.

- Automated Compliance Checking: Developing automated compliance checking systems to ensure design issue documentation meets regulatory requirements before closure, minimizing risks.
- Value Realization Analytics: Implementing analytics to measure the value realized from corrective and preventive actions, providing insights for continuous improvement and future decision-making.

In summary, integrating data science into Issue Management & CAPA enhances agility, fosters collaboration, and drives innovation across the organization. By leveraging advanced analytics, artificial intelligence, and automation technologies, organizations can navigate complexities, capitalize on opportunities, and achieve strategic objectives effectively while ensuring compliance, quality, and stakeholder satisfaction (Balaji et al., 2019; Bargh et al., 2015; Brous et al., 2020; Cohen et al., 2020; Joshi & Krag, 2010; Karim et al., 2016; Tilimbe, 2019).

4.1.1.4 Product & Portfolio Management

Product & Portfolio Management plays a pivotal role in orchestrating the strategic development, optimization, and governance of an organization's product offerings and portfolio.

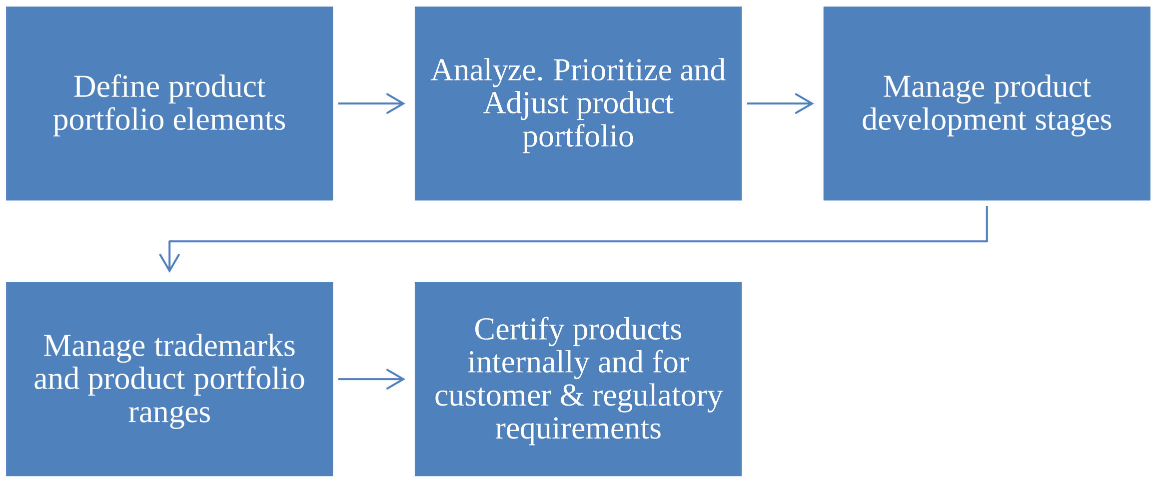

Figure 5 Typical product and portfolio management process flow. Source: Author

This function is instrumental in aligning product development initiatives with market demands, customer preferences, regulatory requirements, and organizational objectives. Below sections will discuss the various activities shown in figure 5 and data science use cases applicable in these activities.

Define Product Portfolio Elements:

The initial phase involves defining the elements of the product portfolio, including product categories, variants, specifications, features, pricing strategies, and target markets. This establishes a foundational framework for product development, positioning, and market entry. Below are some data science use cases for defining product portfolio elements:

- Market Segmentation Analysis: Using data science to identify distinct customer segments based on demographics, behavior, and preferences, informing targeted product categories and pricing strategies.
- Demand Forecasting: Employing predictive analytics to forecast demand for different product variants and categories, optimizing inventory management and production planning.
- Conjoint Analysis: Utilizing conjoint analysis to understand customer preferences for various product features and attributes, guiding decisions on product specifications and variants.
- Price Optimization: Applying machine learning algorithms to optimize pricing strategies based on market dynamics, competitor pricing, and customer willingness to pay.
- Feature Importance Analysis: Conducting feature importance analysis to determine the most influential product features and specifications driving customer satisfaction and market demand.

Analyze, Prioritize, and Adjust Product Portfolio: Comprehensive analysis, prioritization, and adjustment of the product portfolio are conducted based on factors such as market trends, competitive landscape, customer feedback, financial performance, and strategic alignment. This ensures optimal resource allocation, risk mitigation, and alignment with organizational goals and market demands. Below are some data science use cases:

- Market Segmentation Analysis: Using data science to segment customers based on their preferences and behaviors, informing targeted product portfolio adjustments.
- Predictive Analytics for Demand Forecasting: Leveraging predictive analytics to forecast future demand for products, guiding portfolio adjustments to meet market needs.
- Competitor Analysis and Benchmarking: Employing data-driven methods to analyze competitor offerings and market positioning, informing strategic adjustments to the product portfolio.
- Customer Sentiment Analysis: Analyzing customer feedback and sentiment data to prioritize product improvements and adjustments based on customer preferences.

- Portfolio Optimization Algorithms: Applying optimization algorithms to allocate resources effectively across the product portfolio, maximizing profitability and strategic alignment.

Manage Product Development Stages: Effective management of product development stages, from ideation and concept validation to design, prototyping, testing, production, and launch, ensures seamless execution, quality assurance, and timely market entry. This involves cross-functional collaboration, stakeholder engagement, and adherence to regulatory requirements throughout the product lifecycle. Below are some data science use cases:

- Predictive Analytics for Market Demand: Forecasting market demand for the product using predictive analytics to optimize production schedules and inventory management.
- Machine Learning for Design Optimization: Implementing machine learning algorithms to optimize product design parameters based on performance, cost, and customer feedback.
- Failure Prediction Models: Developing models to predict potential failures during product testing stages, enabling proactive maintenance and quality assurance.
- Supply Chain Optimization: Utilizing data science techniques to optimize the supply chain by identifying inefficiencies, minimizing costs, and ensuring timely delivery of components.
- Regulatory Compliance Monitoring: Developing tools to monitor regulatory compliance throughout the product development lifecycle, ensuring adherence to standards and requirements.

Manage Trademarks and Product Portfolio Ranges: Strategic management of trademarks, patents, copyrights, and intellectual property rights associated with the product portfolio safeguards organizational assets, enhances brand equity, and ensures compliance with legal and regulatory frameworks. This involves monitoring, renewal, enforcement, and optimization of intellectual property assets across diverse markets and jurisdictions.
Below are some data science use cases:

- Trademark Monitoring and Detection: Utilizing machine learning algorithms to monitor online and offline channels for trademark infringements and unauthorized usage, ensuring brand protection.
- Patent Portfolio Analysis: Applying data analytics to analyze and optimize patent portfolios, identifying opportunities for licensing, divestment, or acquisition to maximize value.
- Copyright Compliance Automation: Developing automated systems to monitor and enforce copyright compliance, detecting and addressing unauthorized use of copyrighted materials.
- Intellectual Property Risk Assessment: Employing data-driven risk assessment models to evaluate potential risks to intellectual property assets and prioritize mitigation efforts.
- Market Analysis for IP Strategy: Using data science techniques to analyze market trends, competitor activities, and consumer behaviors to inform intellectual property strategy and portfolio management decisions.

Certify Products Internally and for Customer & Regulatory Requirements: Certification processes, both internally and externally, are conducted to validate product quality, safety, performance, and compliance with customer specifications, industry standards, and regulatory requirements. This involves rigorous testing, validation, documentation, and stakeholder communication to ensure product integrity and market acceptance.

Below are some data science use cases:

- Predictive Modeling for Quality Assurance: Using predictive models to forecast product quality issues based on historical data, enhancing proactive quality assurance measures.
- Anomaly Detection in Testing Data: Employing anomaly detection algorithms to identify irregularities or deviations in testing data, flagging potential quality or safety concerns.

- Regulatory Compliance Monitoring: Developing algorithms to continuously monitor changes in regulatory requirements and assess product compliance, ensuring adherence to evolving standards.
- Image Recognition for Defect Detection: Implementing image recognition algorithms to automatically detect defects or anomalies in product components during manufacturing processes.
- Natural Language Processing (NLP) for Compliance Documentation: Applying NLP techniques to analyze and extract relevant information from regulatory documents, facilitating compliance documentation and reporting.
- Simulation and Modeling for Performance Testing: Utilizing simulation and modeling techniques to simulate real-world scenarios and conduct performance testing, predicting product behavior under different conditions.
- Supply Chain Risk Assessment: Using data analytics to assess risks within the supply chain and mitigate potential disruptions to product certification processes.
- Predictive Maintenance for Equipment Reliability: Employing predictive maintenance models to anticipate equipment failures or malfunctions that could impact product certification processes.
- Customer Feedback Analysis: Analyzing customer feedback and complaints using sentiment analysis to identify areas for improvement and enhance product certification processes.
- Predictive Analytics for Market Acceptance: Leveraging predictive analytics to forecast market acceptance of certified products based on customer preferences, competitive landscape, and industry trends.

In summary, integrating data science into Product & Portfolio Management enhances agility, fosters collaboration, drives innovation, and ensures compliance across the product lifecycle. By leveraging advanced analytics, artificial intelligence, and automation technologies, organizations can navigate complexities, capitalize on opportunities, mitigate risks, and achieve strategic objectives effectively while maximizing customer value, market share, and profitability (Mehlstaubl et al., 2021; Otten et al., 2015; Tucker & Kim, 2009).

4.1.1.5 Product Line Variability

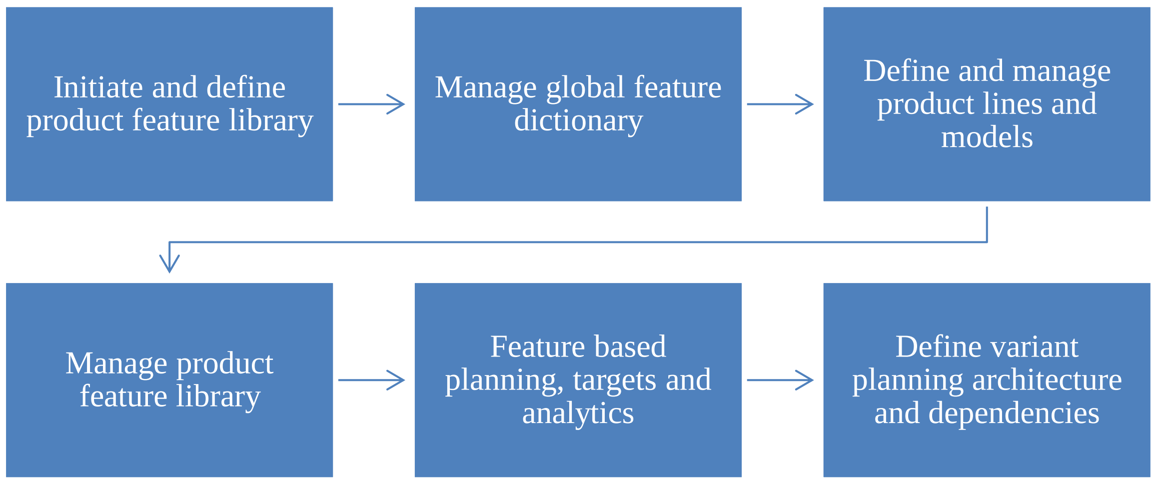

Figure 6 Typical product line variability management process flow. Source: Author

Product Line Variability focuses on managing the diversity of products within an organization's portfolio, ensuring flexibility, customization, and alignment with market demands, customer preferences, and strategic objectives. This function encompasses various sub-functions that are critical to optimizing product line configurations, feature sets, and market positioning. Below sections will discuss the various activities shown in figure 6 and data science use cases applicable in these activities.

Initiate and Define Product Feature Library: The initial step involves initiating and defining a comprehensive product feature library that encompasses various features, specifications, configurations, and options available across different product lines and models. This facilitates standardization, customization, and modularization of product offerings based on customer requirements, market trends, and competitive dynamics.

Below are some data science use cases for initiating and defining a product feature library:

- Cluster Analysis for Feature Segmentation

- Predictive Analytics for Feature Demand Forecasting
- Recommendation Systems for Feature Bundling
- Market Basket Analysis for Feature Association
- Text Mining for Feature Extraction from Customer Feedback
- Competitive Analysis using Feature Diffusion Models
- A/B Testing for Feature Prioritization
- Sentiment Analysis for Feature Perception Monitoring
- Feature Importance Analysis using Machine Learning Models
- Customer Segmentation based on Feature Preferences
- Trend Analysis for Feature Adoption Patterns
- Collaborative Filtering for Feature Recommendations
- Customer Lifetime Value Prediction based on Feature Usage
- Feature Interaction Analysis using Regression Models
- Dynamic Pricing Models based on Feature Value Perception

Manage Global Feature Dictionary: Strategic management of a global feature dictionary enables organizations to standardize terminology, classifications, attributes, and specifications across diverse product lines, markets, and regions. This ensures consistency, interoperability, and alignment with organizational goals, industry standards, and regulatory requirements. Below are some data science use cases:

- Automated feature extraction and classification.
- Natural language processing for standardizing terminology.
- Ontology development and maintenance.
- Clustering analysis for identifying similar features.
- Data governance and quality assurance.
- Semantic similarity measurement.
- Entity resolution and deduplication.
- Collaborative filtering for feature recommendation.
- Hierarchical feature taxonomy development.

- Version control and change tracking for feature dictionary updates.

Define and Manage Product Lines and Models:

Clear definition and management of product lines and models involve categorizing, segmenting, and aligning products based on market segments, customer profiles, lifecycle stages, and strategic priorities. This facilitates portfolio optimization, resource allocation, and market penetration strategies tailored to specific target audiences and market dynamics. Below are some data science use cases:

- Market Segmentation Analysis
- Customer Profiling and Clustering
- Product Lifecycle Prediction
- Demand Forecasting
- Competitive Analysis and Benchmarking
- Price Elasticity Modeling
- Recommender Systems for Cross-Selling and Upselling
- Product Portfolio Optimization
- Churn Prediction and Customer Retention Strategies
- Sales Forecasting and Inventory Management

Manage Product Feature Library:

Ongoing management, updates, and maintenance of the product feature library ensure alignment with evolving customer preferences, technological advancements, regulatory changes, and competitive landscapes. This involves collaboration with cross-functional teams, stakeholders, suppliers, and partners to ensure relevance, scalability, and sustainability of product offerings. Below are some data science use cases:

- Product Feature Prioritization
- Customer Segmentation for Feature Preferences
- Predictive Analytics for Feature Adoption
- Feature Recommendation Systems
- Sentiment Analysis of Feature Feedback

- Market Basket Analysis for Feature Bundling
- Feature Usage Analytics
- Competitor Feature Analysis
- Feature Impact Analysis

Feature-Based Planning, Targets, and Analytics:

Strategic planning, setting targets, and leveraging analytics based on product features enable organizations to optimize resource allocation, prioritize initiatives, and drive innovation across product lines and models. This involves utilizing data-driven insights, market intelligence, customer feedback, and performance metrics to inform decision-making, mitigate risks, and capitalize on opportunities effectively. Below are some data science use cases:

- Feature Importance Analysis
- Predictive Modeling for Feature Adoption
- Customer Segmentation based on Feature Usage
- Feature-based Market Basket Analysis
- Feature-based Cohort Analysis
- Feature-based A/B Testing
- Feature-based Sentiment Analysis
- Feature-based Customer Lifetime Value Prediction
- Feature-based Churn Prediction
- Feature-based Pricing Optimization

Define Variant Planning Architecture and Dependencies:

Establishing a variant planning architecture and managing dependencies across product lines, models, features, and configurations ensure coherence, compatibility, and consistency in product development, manufacturing, distribution, and service delivery processes. This involves identifying, analyzing, and optimizing dependencies, constraints, and interdependencies to enhance agility, flexibility, and responsiveness to market demands and customer requirements. Below are some data science use cases:

- Predictive Modeling for Demand Forecasting

- Network Analysis for Dependency Mapping
- Optimization Algorithms for Resource Allocation
- Machine Learning for Feature Selection
- Simulation Modeling for Scenario Analysis
- Clustering Analysis for Product Segmentation
- Natural Language Processing for Requirement Extraction
- Decision Trees for Dependency Identification
- Time Series Analysis for Trend Forecasting
- Graph Databases for Dependency Management

In summary, integrating data science into Product Line Variability enhances agility, fosters collaboration, drives innovation, and ensures compliance across the product lifecycle. By leveraging advanced analytics, artificial intelligence, and automation technologies, organizations can navigate complexities, capitalize on opportunities, mitigate risks, and achieve strategic objectives effectively while maximizing customer value, market share, and profitability (Abo Zaid & De Troyer, 2011; Bachmann & Clements, 2005; Heider et al., 2012; Kastner et al., 2014; Nestor et al., 2007; Roos-Frantz et al., 2012).

4.1.1.6 Standards, Global Attributes & Parameter Management

Standards, Global Attributes & Parameter Management is a critical function responsible for establishing, maintaining, and governing the standardized attributes, parameters, and guidelines that define products, processes, and systems within an organization. This function ensures consistency, interoperability, compliance, and alignment with industry standards, regulatory requirements, corporate strategies, and stakeholder expectations. Below sections will discuss about the various activities shown in *figure 7* and data science use cases applicable in these activities.

Manage Model Parameters in Dictionaries: This involves the management, documentation, and governance of model parameters in centralized dictionaries or repositories, ensuring consistency, accuracy, and accessibility across various departments, projects, and domains. A list of data science use cases for managing model parameters in dictionaries is given below:

- Automated parameter validation and cleansing.
- Predictive modeling for parameter optimization.
- Anomaly detection for identifying irregularities in parameter values.
- Clustering analysis for grouping similar parameters.
- Recommendation systems for suggesting relevant parameters based on context.

Manage Measurable Attribute Definitions in Libraries: Effective management of measurable attribute definitions involves defining, classifying, documenting, and maintaining attribute libraries that capture essential characteristics, specifications, tolerances, and criteria relevant to products, processes, and services. A list of data Science use case for this activity is given below:

- Data-driven attribute classification and tagging.
- Automated attribute documentation generation.
- Predictive maintenance for attribute libraries.
- Attribute similarity analysis for consolidation.
- Attribute quality control using anomaly detection.
- Measurable attribute recommendation systems.
- Attribute trend analysis for forecasting.

Define and Classify Standard: This sub-function focuses on defining, classifying, and categorizing standards based on industry best practices, regulatory requirements, technological advancements, and organizational objectives. This ensures clarity, consistency, and compliance across diverse domains, projects, and stakeholders. A list of data Science use case for this activity is given below:

- Predictive Analytics for Standard Adoption Rates
- Text Classification for Standard Document Organization

- Clustering Algorithms for Standard Similarity Analysis
- Topic Modeling for Standard Topic Identification
- Recommender Systems for Standard Selection

Define Access and Usage: Establishing clear guidelines, protocols, and permissions for accessing and utilizing standards, attributes, and parameters ensures security, confidentiality, integrity, and accountability within the organization. This involves defining roles, responsibilities, workflows, and approval processes tailored to specific requirements and regulatory mandates. A list of data Science use case for this activity is given below:

- Role-Based Access Control (RBAC) Modeling
- Anomaly Detection in Access Patterns
- Predictive Maintenance for Standards Management Systems
- User Behavior Analytics for Security Monitoring
- Automated Workflow Optimization
- Natural Language Processing (NLP) for Policy Analysis
- Dynamic Permission Assignment Algorithms
- Fraud Detection in Permissions and Access Requests
- Continuous Compliance Monitoring with Machine Learning
- Predictive Analytics for Approval Process Optimization

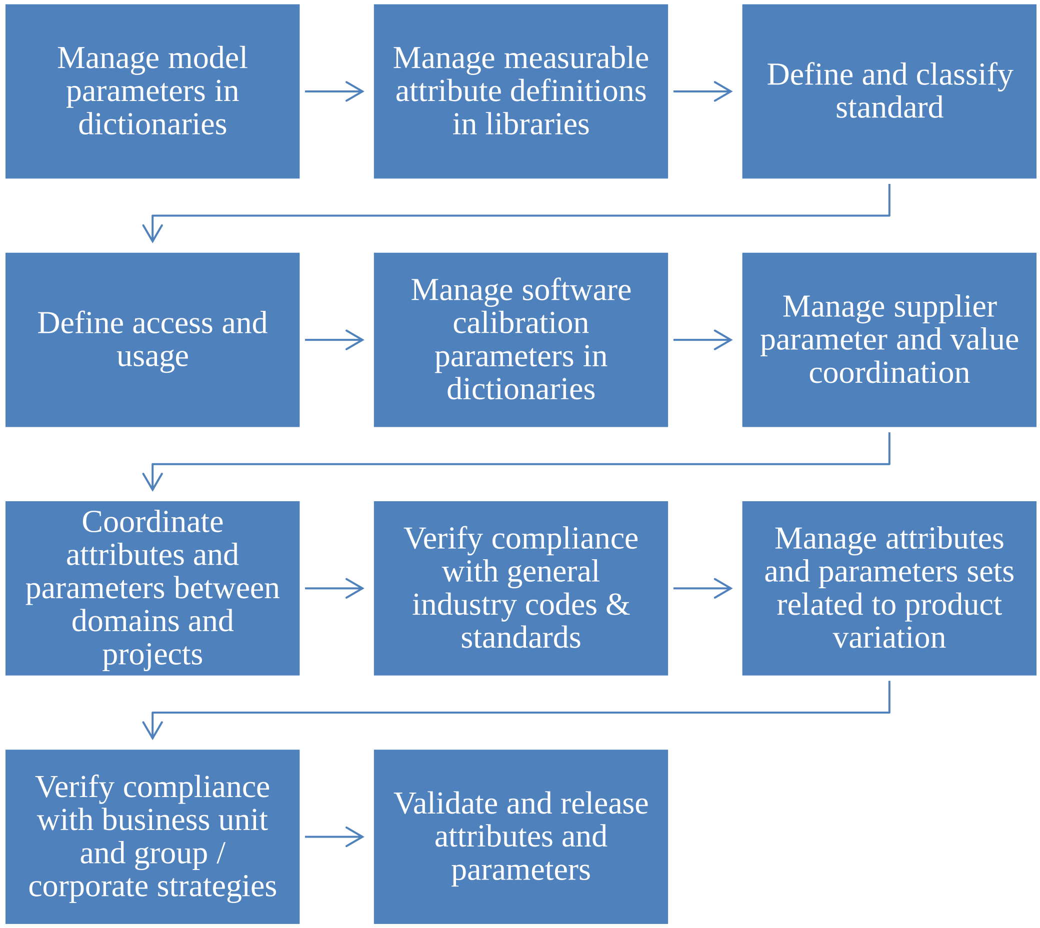

Figure 7 Typical Standards, Global Attribute, and parameter management process flow.

Source: Author

Manage Software Calibration Parameters in Dictionaries: This involves managing, calibrating, and validating software parameters in dictionaries or databases to ensure accuracy, reliability, performance, and compliance with industry standards, customer specifications, and organizational requirements. A list of data Science use case for this activity is given below:

- Anomaly Detection
- Predictive Maintenance Models
- Automated Quality Assurance
- Optimization Algorithms
- Time Series Analysis

Manage Supplier Parameter and Value Coordination:

Coordination with suppliers to manage parameter values, specifications, tolerances, and requirements ensures alignment, consistency, quality assurance, and collaboration across the supply chain, value stream, and ecosystem. A list of data Science use case for this activity is given below:

- Predictive modeling for demand forecasting
- Anomaly detection in supplier data
- Supplier segmentation based on performance metrics.
- Optimization of inventory levels using machine learning algorithms
- Sentiment analysis of supplier communications
- Predictive maintenance for supplier equipment
- Automated supplier performance evaluation
- Fraud detection in supplier transactions
- Dynamic pricing models for supplier negotiations
- Predictive analytics for supplier risk assessment

Coordinate Attributes and Parameters Between Domains and Projects:

Effective coordination between domains, projects, departments, and stakeholders ensures alignment, interoperability, collaboration, and synergy in managing attributes, parameters, standards, and guidelines across the organization. A list of data Science use case for this activity is given below:

- Data Integration and Fusion
- Cross-Domain Data Mapping
- Semantic Data Harmonization
- Interoperability Analysis
- Cross-Domain Attribute Matching

Verify Compliance with General Industry Codes & Standards:

Regular verification, validation, and auditing of compliance with general industry codes, standards, regulations, and best practices ensure adherence, accountability, and governance within the organization. A list of data Science use case for this activity is given below:

- Anomaly Detection
- Predictive Modeling
- Text Mining
- Classification Algorithms
- Clustering Analysis

Manage Attributes and Parameters Sets Related to Product Variation:

This involves managing attribute and parameter sets related to product variations, configurations, options, features, and customizations to meet diverse customer requirements, market demands, and regulatory constraints. A list of data Science use case for this activity is given below:

- Predictive Modeling for Demand Forecasting
- Customer Segmentation and Targeting
- Product Recommendation Systems
- Predictive Maintenance Models
- Dynamic Pricing Optimization

Verify Compliance with Business Unit and Group / Corporate Strategies:

Alignment with business unit, group, and corporate strategies ensures coherence, consistency, alignment, and synergy in managing attributes, parameters, standards, and guidelines across the organization. A list of data Science use case for this activity is given below:

- Predictive Analytics for Strategy Alignment
- Text Mining for Strategy Documentation Analysis

- Network Analysis for Identifying Strategy Dependencies
- Machine Learning for Strategy Performance Prediction
- Clustering Analysis for Strategy Segmentation

Validate and Release Attributes and Parameters:
This involves validating, approving, and releasing attributes and parameters based on rigorous testing, evaluation, analysis, review, and approval processes to ensure quality, reliability, performance, and compliance. A list of data Science use case for this activity is given below:

- Predictive Analytics for Strategy Alignment Assessment
- Natural Language Processing (NLP) for Strategy Document Analysis
- Machine Learning for Strategy Recommendation Systems
- Text Mining for Strategy Gap Identification
- Clustering Analysis for Strategy Segmentation

In summary, integrating data science into Standards, Global Attributes & Parameter Management enhances agility, fosters collaboration, drives innovation, ensures compliance, and maximizes value across the organization. By leveraging advanced analytics, artificial intelligence, automation technologies, and predictive modeling, organizations can navigate complexities, capitalize on opportunities, mitigate risks, and achieve strategic objectives effectively while enhancing stakeholder satisfaction, trust, and loyalty (Hill, 2012; Wang et al., 2013).

4.1.1.7 Content and Document Management

Content and Document Management is a critical function responsible for creating, organizing, storing, accessing, sharing, and managing documentation and content across various domains, projects, departments, and stakeholders within an organization. This function ensures consistency, accuracy, compliance, accessibility, and security of information, knowledge, and intellectual assets. Below are the key sub-functions as shown in *figure 8* integral to Content and Document Management:

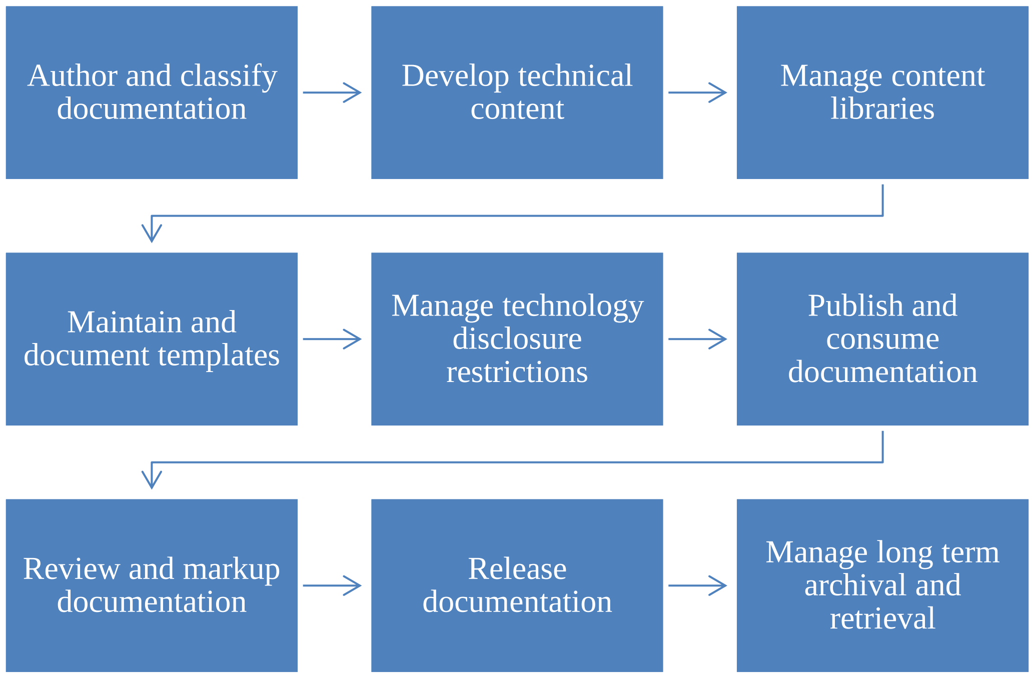

Figure 8 Typical Content and Document Management process flow. Source: Author

Author and Classify Documentation:

This involves creating, authoring, categorizing, tagging, and classifying documentation based on content type, format, purpose, audience, relevance, and lifecycle stages. It ensures consistency, structure, metadata tagging, and accessibility across diverse repositories, platforms, and stakeholders. A list of data Science use case for this activity is given below:

- Automated Document Categorization
- Text Classification for Content Tagging
- Metadata Extraction for Document Organization
- Topic Modeling for Content Classification
- Content Recommendation Systems

Develop Technical Content:

Creating, developing, updating, and maintaining technical content, such as specifications, guidelines, procedures, manuals, standards, best practices, and knowledge bases, ensures accuracy, relevance, comprehensiveness, and usability for targeted audiences, projects, and initiatives. A list of data Science use case for this activity is given below:

- Natural Language Generation (NLG) for Automated Documentation Generation
- Content Recommendation Systems
- Knowledge Base Quality Assurance through Text Analytics
- Topic Modeling for Content Organization
- Sentiment Analysis for User Feedback on Technical Content
- Content Personalization using Machine Learning Algorithms
- Text Summarization for Technical Documents
- Named Entity Recognition (NER) for Content Tagging and Categorization
- Automated Translation of Technical Content
- Content Performance Analytics using Predictive Modeling

Manage Content Libraries:

Organizing, curating, indexing, archiving, and updating content libraries, repositories, databases, and knowledge bases enable efficient storage, retrieval, sharing, collaboration, and reuse of information, resources, and intellectual assets across the organization. A list of data Science use case for this activity is given below:

- Automated tagging and categorization of documents using machine learning.
- Content recommendation systems based on user preferences and behaviors.
- Natural Language Processing (NLP) for content summarization.
- Sentiment analysis of document comments and feedback.
- Predictive analytics for content demand forecasting.

Maintain and Document Templates:

Designing, maintaining, updating, and documenting templates, formats, layouts, styles, and guidelines ensure consistency, efficiency, standardization, and compliance in creating, formatting, and publishing documentation across various domains, projects, and stakeholders. A list of data Science use case for this activity is given below:

- Template Recommendation Systems
- Template Version Control and Change Tracking
- Template Usage Analytics
- Automated Template Generation
- Template Performance Monitoring and Optimization

Manage Technology Disclosure Restrictions:

Implementing and enforcing technology disclosure restrictions, confidentiality agreements, intellectual property rights, and regulatory compliance requirements ensure security, confidentiality, integrity, and compliance in managing sensitive, proprietary, and restricted information. A list of data Science use case for this activity is given below:

- Natural Language Processing (NLP) for Contract Analysis
- Entity Recognition for Identifying Intellectual Property References
- Classification Models for Document Sensitivity Labeling
- Anomaly Detection for Unauthorized Access Detection
- Privacy-Preserving Techniques for Data Sharing Compliance

Publish and Consume Documentation:

Facilitating the publishing, distribution, dissemination, sharing, and consumption of documentation across internal and external stakeholders, platforms, and channels ensures accessibility, visibility, collaboration, and engagement in knowledge sharing, communication, and decision-making processes. A list of data Science use case for this activity is given below:

- Document Recommendation Systems
- Content Personalization Algorithms
- Document Version Control Automation
- Document Metadata Extraction and Analytics
- Content Usage Analytics

Review and Markup Documentation:

Conducting reviews, revisions, annotations, markups, approvals, and validations of documentation by subject matter experts, stakeholders, reviewers, and authorities ensures quality, accuracy, completeness, relevance, and compliance in content development, management, and dissemination. A list of data Science use case for this activity is given below:

- Natural Language Processing (NLP) for Automated Review Summaries
- Sentiment Analysis for Reviewer Feedback
- Document Version Control and Change Tracking
- Document Similarity Analysis for Content Comparison
- Automated Markup Suggestions Using Machine Learning

Release Documentation:

Formalizing, approving, releasing, distributing, and archiving documentation based on predefined workflows, processes, templates, standards, and guidelines ensures consistency, traceability, accountability, and compliance in content lifecycle management across the organization. A list of data Science use case for this activity is given below:

- Automated Document Tagging
- Document Version Control
- Document Classification
- Content Recommendation Systems
- Natural Language Processing for Document Summarization

Manage Long Term Archival and Retrieval:

Establishing, maintaining, and managing long-term archival, retrieval, storage, backup, preservation, and disposition strategies, policies, and procedures for documentation and content ensure sustainability, accessibility, compliance, and continuity of information assets over time. A list of data Science use case for this activity is given below:

- Predictive Analytics for Content Usage Trends
- Automated Metadata Extraction and Tagging
- Anomaly Detection for Document Access Patterns

- Natural Language Processing for Document Search and Retrieval
- Machine Learning Models for Content Classification and Categorization

In summary, integrating data science into Content and Document Management enhances agility, fosters collaboration, drives innovation, ensures compliance, and maximizes value across the organization. By leveraging advanced analytics, artificial intelligence, automation technologies, and predictive modeling, organizations can navigate complexities, capitalize on opportunities, mitigate risks, and achieve strategic objectives effectively while enhancing stakeholder satisfaction, trust, and loyalty (Qin & D'ignazio, 2010; Rajasekar & Moore, 2001; Scott, 2015; Virkus & Garoufallou, 2019).

4.1.1.8 Intellectual Property Management

Intellectual Property (IP) Management is a crucial function responsible for safeguarding, managing, and maximizing the value of an organization's intellectual assets, including patents, trademarks, copyrights, trade secrets, and proprietary information. This function ensures compliance with legal regulations, protection against infringement, optimization of asset utilization, and enhancement of competitive advantage. Below are the key sub-functions as shown in *figure 9* integral to Intellectual Property Management:

Manage Security Classification:

This involves categorizing, classifying, labeling, and safeguarding intellectual assets based on their sensitivity, value, confidentiality, accessibility, and exposure risks. It ensures appropriate protection measures, access controls, encryption, and security protocols are implemented to prevent unauthorized access, disclosure, alteration, or misuse. A list of data Science use case for this activity is given below:

- Automated Classification using Machine Learning
- Predictive Analytics for Identifying Potential Security Risks
- Anomaly Detection for Unauthorized Access Detection
- Natural Language Processing for Document Labeling and Tagging
- Network Traffic Analysis for Monitoring Data Flows and Access Patterns

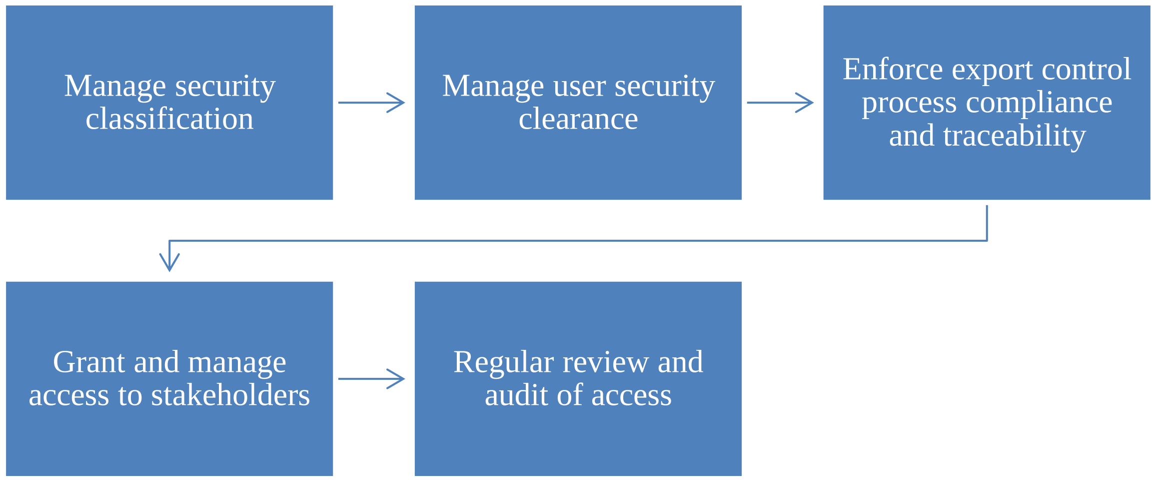

Figure 9 Typical Intellectual Property Management process flow. Source: Author

Manage User Security Clearance:

Establishing, enforcing, and managing user security clearance levels, roles, permissions, and access controls ensure that authorized personnel have appropriate privileges to access, modify, distribute, and utilize intellectual assets based on their roles, responsibilities, and requirements. It involves implementing identity management, authentication, authorization, and audit trails to track and monitor user activities. A list of data Science use case for this activity is given below:

- User Behavior Analytics
- Anomaly Detection
- Identity Verification
- Access Pattern Analysis
- Role-Based Access Control (RBAC) Optimization

Enforce Export Control Process Compliance and Traceability:

Ensuring compliance with export control laws, regulations, and international treaties requires establishing, enforcing, and monitoring export control processes, protocols, documentation, reporting, and traceability mechanisms. It involves screening, classifying, licensing, and tracking exports of intellectual assets to prevent unauthorized transfers, disclosures, or violations of legal requirements. A list of data Science use case for this activity is given below:

- Natural Language Processing (NLP) for Screening and Classification
- Machine Learning Models for License Prediction
- Network Analysis for Tracking Export Activities
- Anomaly Detection for Unauthorized Transfer Detection
- Predictive Analytics for Compliance Monitoring

Grant and Manage Access to Stakeholders:

Facilitating and managing access to intellectual assets for internal and external stakeholders, partners, collaborators, customers, regulators, and authorities require establishing, documenting, approving, and monitoring access rights, permissions, roles, and responsibilities based on contractual agreements, legal requirements, business needs, and security considerations. A list of data Science use case for this activity is given below:

- Access Control Optimization
- Role-Based Access Control (RBAC) Implementation
- Access Pattern Analysis
- Access Request Prediction
- Access Monitoring and Anomaly Detection

Regular Review and Audit of Access:

Conducting periodic reviews, audits, assessments, and evaluations of access rights, permissions, activities, and compliance with intellectual property policies, procedures, guidelines, and regulations ensures accountability, transparency, integrity, and adherence to best practices within the organization. A list of data Science use case for this activity is given below:

- Anomaly Detection
- Access Pattern Analysis
- User Behaviour Modelling

- Compliance Monitoring
- Predictive Analytics

In summary, integrating data science into Intellectual Property Management enhances agility, fosters collaboration, drives innovation, ensures compliance, and maximizes value across the organization. By leveraging advanced analytics, artificial intelligence, automation technologies, and predictive modeling, organizations can navigate complexities, capitalize on opportunities, mitigate risks, and achieve strategic objectives effectively while enhancing stakeholder satisfaction, trust, and loyalty (Geller, 2010; Gervais, 2019; Seng, 2021; Wang, 2020; Yang, 2019).

4.1.1.9 Partner & Customer Collaboration

Partner & Customer Collaboration is a pivotal function that focuses on fostering strong relationships, enhancing communication, ensuring alignment, and delivering value to partners and customers through effective collaboration, coordination, and cooperation. This function facilitates the exchange of information, knowledge, resources, insights, feedback, and solutions to achieve mutual objectives, resolve issues, and capitalize on opportunities.

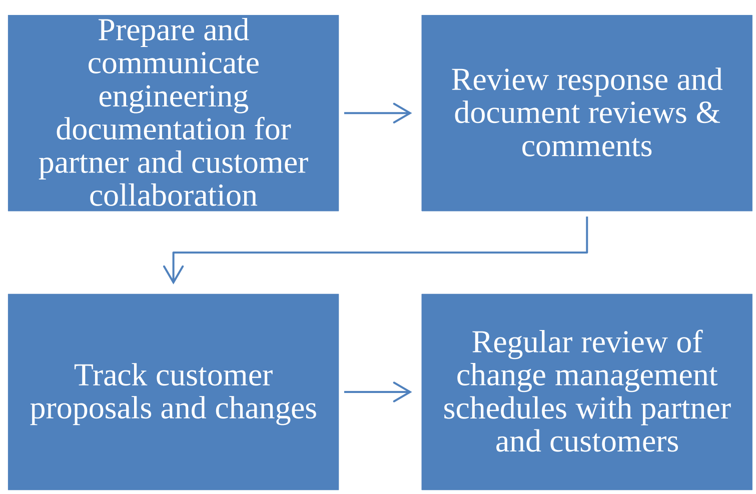

Figure 10 Typical Partner & Customer Collaboration process flow. Source: Author

Below are the key sub-functions as shown in *figure 10* integral to Partner & Customer Collaboration:

Prepare and Communicate Engineering Documentation for Partner and Customer Collaboration:

This involves creating, organizing, formatting, reviewing, approving, and distributing engineering documentation, such as specifications, requirements, designs, plans, guidelines, manuals, and reports, to partners and customers. It ensures clarity, consistency, accessibility, relevance, and timeliness in sharing critical information and resources for collaboration, integration, customization, implementation, and support. Few Data Science use cases for the above activities are listed below.

- Natural Language Processing (NLP) for Document Summarization: Using NLP techniques to summarize large engineering documents, making them more accessible and digestible for partners and customers.
- Document Classification and Tagging: Implementing machine learning models to automatically classify engineering documents based on content, making it easier to organize and retrieve relevant information.
- Version Control and Change Tracking: Utilizing data science to implement version control systems that track changes in engineering documents, ensuring clarity and consistency in collaboration efforts.
- Recommendation Systems: Building recommendation systems that suggest relevant engineering documents to partners and customers based on their previous interactions and interests, enhancing collaboration efficiency.
- Document Similarity Analysis: Employing techniques like cosine similarity to identify similar documents, enabling partners and customers to find related information quickly and accurately.

Review Response and Document Reviews & Comments:

Evaluating, analyzing, addressing, incorporating, and documenting partner and customer responses, reviews, comments, feedback, suggestions, and requirements regarding engineering documentation, proposals, changes, solutions, and deliverables ensure alignment, satisfaction, quality, compliance, and continuous improvement in collaboration efforts. Few Data Science use cases for the above activities are listed below.

- Sentiment Analysis: Using sentiment analysis to gauge the sentiment of partner and customer comments on engineering documents, allowing for more targeted and effective responses.
- Topic Modeling: Applying topic modeling algorithms to identify common themes or topics in reviews and comments, helping prioritize issues and suggestions for improvement.
- Collaborative Filtering: Implementing collaborative filtering techniques to prioritize partner and customer feedback based on the preferences and behaviors of similar users, improving responsiveness to their needs.
- Automated Response Generation: Developing algorithms to automatically generate responses to common queries and comments, speeding up the review process and improving customer satisfaction.
- Feedback Analysis Dashboard: Creating dashboards that visualize partner and customer feedback trends over time, enabling proactive identification of emerging issues and opportunities for improvement.

Track Customer Proposals and Changes:

Monitoring, updating, communicating, and coordinating customer proposals, changes, requirements, expectations, commitments, schedules, milestones, deliverables, and outcomes enable proactive management, alignment, negotiation, adaptation, and fulfillment of contractual obligations and service level agreements with partners and customers. Few Data Science use cases for the above activities are listed below.

- Predictive Analytics for Proposal Acceptance: Using predictive analytics to forecast the likelihood of customer proposal acceptance based on historical data and contextual factors, aiding in decision-making and negotiation strategies.
- Change Impact Analysis: Employing data science techniques to assess the potential impact of proposed changes on project timelines, budgets, and resource allocation, facilitating informed decision-making and risk management.

- Customer Segmentation: Segmenting customers based on their proposal preferences and behaviors using clustering algorithms, allowing for targeted communication and tailored proposal offerings.
- Dynamic Pricing Models: Developing dynamic pricing models that adjust proposal pricing based on customer characteristics, market conditions, and historical data, optimizing revenue and competitiveness.
- Proposal Performance Monitoring: Implementing key performance indicators (KPIs) and analytics dashboards to track the performance of customer proposals in terms of acceptance rates, conversion rates, and revenue generated.

Regular Review of Change Management Schedules with Partner and Customers: Conducting periodic reviews, assessments, evaluations, discussions, negotiations, and updates of change management schedules, plans, priorities, risks, issues, dependencies, constraints, resources, timelines, and impacts with partners and customers ensure transparency, accountability, flexibility, responsiveness, and alignment in collaboration efforts. Few Data Science use cases for the above activities are listed below.

- Predictive Maintenance Models: Using predictive maintenance models to anticipate potential schedule disruptions caused by equipment failures or maintenance issues, enabling proactive schedule adjustments and mitigating delays.
- Optimization Algorithms: Applying optimization algorithms to optimize resource allocation and scheduling, ensuring efficient use of resources and adherence to change management schedules.
- Risk Prediction and Mitigation: Developing risk prediction models to identify potential risks to change management schedules, along with mitigation strategies to minimize their impact.
- Real-Time Collaboration Platforms: Implementing real-time collaboration platforms equipped with analytics capabilities to facilitate ongoing discussions, updates, and negotiations on change management schedules.
- Performance Monitoring and Feedback Loops: Establishing performance monitoring systems and feedback loops to continuously evaluate the effectiveness

of change management schedules and adapt them based on partner and customer feedback and performance metrics.

In summary, integrating data science into Partner & Customer Collaboration enhances agility, fosters collaboration, drives innovation, ensures compliance, and maximizes value across the organization. By leveraging advanced analytics, artificial intelligence, automation technologies, and predictive modeling, organizations can navigate complexities, capitalize on opportunities, mitigate risks, and achieve strategic objectives effectively while enhancing stakeholder satisfaction, trust, and loyalty (Grimaldi et al., 2021; Han & Trimi, 2022; Hargreaves et al., 2018; Lu et al., 2021; Mas'udin & Kamara, 2017; Méndez-Aparicio et al., 2021; Simões, 2021).

4.1.1.10 Product Cost Management

Product Cost Management is a critical function that focuses on optimizing the cost structure of products, tools, and services to maximize profitability, competitiveness, and customer value while ensuring quality, compliance, and sustainability. This function encompasses various activities related to cost identification, analysis, comparison, decision-making, reporting, and optimization. Below are the key sub-functions of Product Cost Management as show in *figure 11*:

Identify Make Products / Tools:

Identifying in-house manufacturing capabilities, resources, technologies, skills, capacities, and efficiencies to produce products or tools internally, ensuring cost-effectiveness, quality control, customization, innovation, supply chain integration, and strategic alignment with organizational objectives. Below are some data science use cases for the "Identify Make Products / Tools" sub-function:

- Predictive Maintenance for Manufacturing Equipment
- Demand Forecasting for Raw Materials
- Supply Chain Risk Analysis
- Production Capacity Optimization

- Quality Control Monitoring

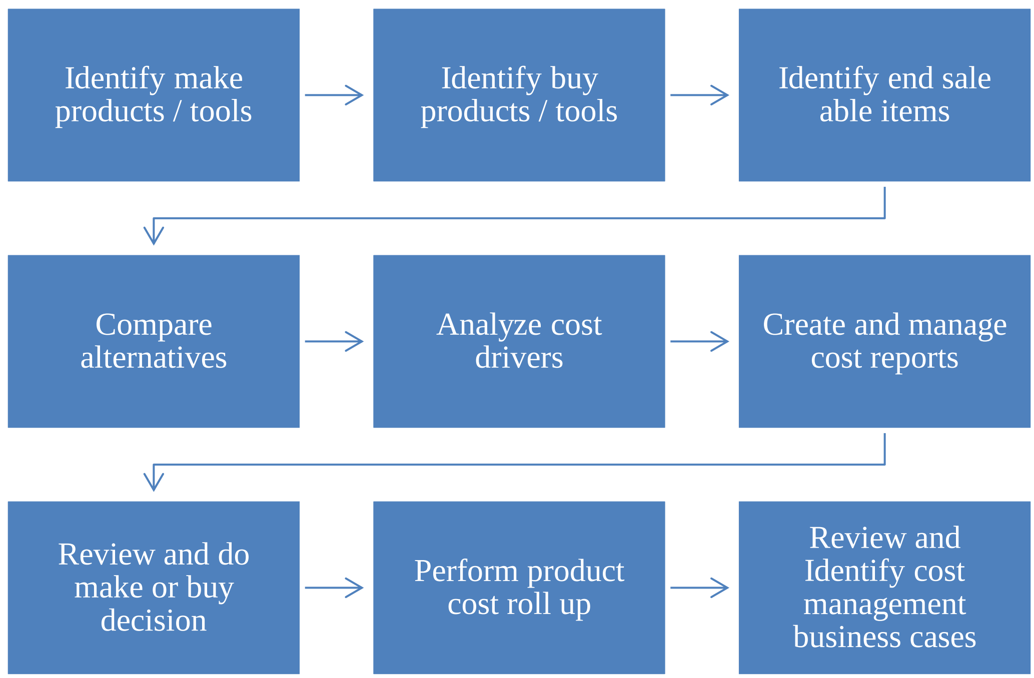

Figure 11 Typical product cost management process flow. Source: Author

Identify Buy Products / Tools:

Evaluating external sourcing options, suppliers, vendors, partners, markets, prices, terms, conditions, risks, opportunities, and trends to procure products or tools externally, ensuring cost-efficiency, scalability, reliability, compliance, innovation, flexibility, and alignment with organizational strategies. Below are some data science use cases for the activity of identifying buy products/tools:

- Predictive Analytics for Supplier Performance
- Supplier Risk Assessment Models
- Market Trend Analysis
- Price Optimization Algorithms
- Demand Forecasting Models

Identify End Saleable Items:

Distinguishing final products, components, assemblies, kits, packages, configurations, versions, options, accessories, services, warranties, licenses, subscriptions, and support offerings that are saleable to customers, distributors, retailers, partners, and end-users, ensuring profitability, marketability, competitiveness, and customer satisfaction.

Data Science use cases:

- Predictive analytics for demand forecasting
- Market basket analysis for product bundling recommendations
- Customer segmentation for targeted pricing strategies
- Predictive maintenance for cost-effective inventory management
- Price optimization models for dynamic pricing strategies

Compare Alternatives:

Analyzing, evaluating, benchmarking, and prioritizing various product, tool, component, material, process, supplier, technology, design, configuration, and manufacturing alternatives based on cost, quality, performance, reliability, sustainability, scalability, availability, lead time, compliance, and strategic fit. Below are some data science use cases for the activity of identifying end saleable items:

- Classification algorithms for categorizing products.
- Clustering techniques for grouping similar products.
- Association rules mining for identifying product bundles.
- Predictive modeling for forecasting demand of different product variations.
- Natural language processing (NLP) for extracting product attributes and features.

Analyze Cost Drivers:

Identifying, quantifying, categorizing, prioritizing, analyzing, mitigating, and optimizing cost drivers, factors, components, elements, variables, constraints, dependencies, risks, uncertainties, and opportunities impacting product cost, profitability, competitiveness, and value creation. Below is a list of data science use cases for the activity of analyzing cost drivers in Product Cost Management:

- Predictive Modeling for Cost Forecasting

- Machine Learning for Cost Prediction
- Regression Analysis for Cost Attribution
- Clustering Analysis for Cost Segmentation
- Anomaly Detection for Cost Identification

Create and Manage Cost Reports:

Generating, updating, maintaining, analyzing, reviewing, sharing, and presenting cost reports, dashboards, metrics, charts, graphs, tables, forecasts, trends, insights, benchmarks, comparisons, and recommendations to facilitate informed decision-making, accountability, transparency, and continuous improvement. Below is a list of data science use cases for the activity of "Create and Manage Cost Reports":

- Predictive Analytics for Cost Forecasting
- Anomaly Detection in Cost Data
- Cost Variance Analysis
- Cost Benchmarking and Comparison
- Cost Optimization Modeling

Review and Do Make or Buy Decision:

Conducting cost-benefit analysis, risk assessment, feasibility study, market research, competitive analysis, supplier evaluation, financial modeling, scenario planning, and strategic alignment to make informed make or buy decisions that optimize cost, quality, time-to-market, innovation, and customer value. Below is a list of data science use cases for the activity of Review and Do Make or Buy Decision:

- Predictive Analytics for Supplier Performance
- Market Basket Analysis for Competitive Analysis
- Supply Chain Optimization
- Predictive Maintenance for Cost Reduction
- Predictive Modeling for Cost Forecasting

Perform Product Cost Roll-Up:

Aggregating, consolidating, summarizing, allocating, attributing, tracking, and reporting individual product costs, components, materials, processes, operations, services, overheads, margins, profits, and risks to determine total product cost, pricing strategy, profitability, and value proposition. Below are some data science use cases for the activity of Perform Product Cost Roll-Up:

- Predictive Analytics for Cost Forecasting
- Cost Attribution Modeling
- Automated Cost Allocation Algorithms
- Optimization of Cost Structures
- Machine Learning for Margin Prediction

Review and Identify Cost Management Business Cases:

Evaluating, prioritizing, approving, funding, monitoring, reviewing, and optimizing cost management initiatives, projects, programs, strategies, tactics, policies, procedures, practices, tools, technologies, and investments based on business cases, ROI, NPV, IRR, payback period, risk-reward ratio, strategic alignment, and organizational priorities. Below are some data science use cases for the activity of reviewing and identifying cost management business cases:

- Predictive Analytics for Cost Forecasting
- Cost-Benefit Analysis Automation
- Optimization Algorithms for Cost Reduction
- Anomaly Detection for Cost Monitoring
- Predictive Maintenance Models for Cost Avoidance

In summary, integrating data science into Product Cost Management enhances agility, fosters collaboration, drives innovation, ensures compliance, and maximizes value across the organization. By leveraging advanced analytics, artificial intelligence, automation technologies, and predictive modeling, organizations can navigate complexities, capitalize on opportunities, mitigate risks, and achieve strategic objectives effectively while enhancing stakeholder satisfaction, trust, and loyalty (Balakrishnan et al., 2011; Cheung et al., 2015; Díaz et al., 2020; Wouters & Stecher, 2017).

4.1.1.11 Advanced Product Quality Planning

Advanced Product Quality Planning (APQP) is a structured framework designed to ensure the development and production of high-quality products that meet or exceed customer expectations while optimizing resources, reducing costs, minimizing risks, and enhancing organizational competitiveness. This section delves into the various sub-functions as shown in *figure 12* integral to APQP and explores the potential applications of data science in enhancing its effectiveness and efficiency.

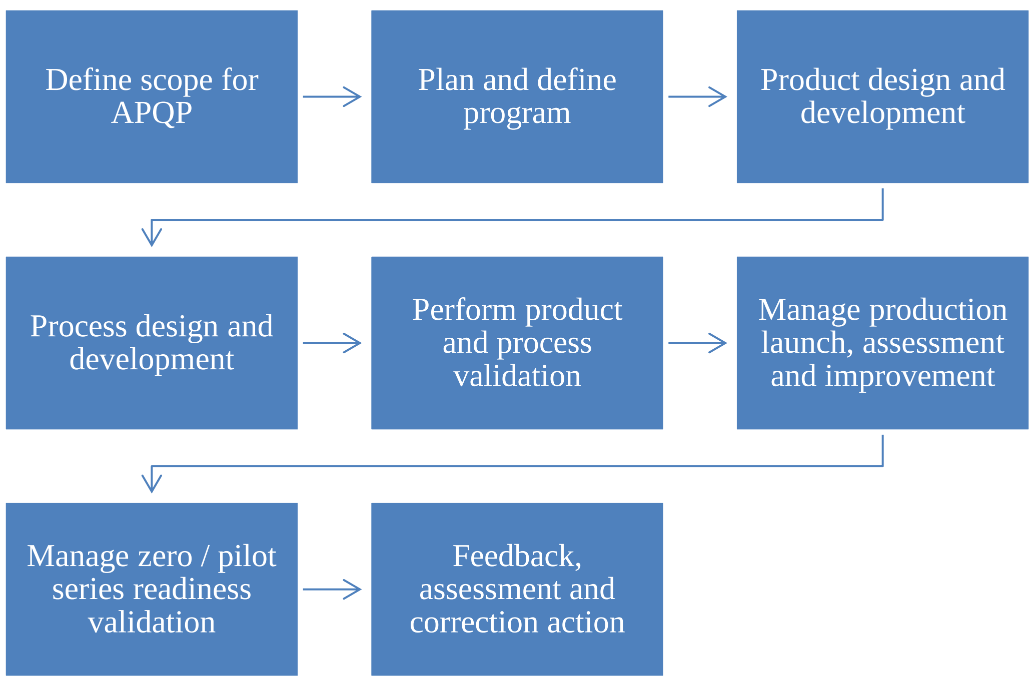

Figure 12 Typical Advanced Product Quality Planning process flow. Source: Author

Define Scope for APQP:

Defining the scope of APQP involves establishing clear objectives, requirements, deliverables, timelines, responsibilities, stakeholders, resources, constraints, risks, opportunities, and success criteria for quality planning and assurance activities throughout the product lifecycle. Data Science use cases:

- Predictive Analytics for Risk Identification
- Automated Resource Allocation Optimization
- Natural Language Processing for Requirement Analysis
- Stakeholder Network Analysis
- Scope Change Detection and Management

Plan and Define Program:

Planning and defining the APQP program entail creating detailed plans, schedules, budgets, milestones, tasks, activities, dependencies, workflows, communication strategies, documentation, tools, techniques, methodologies, and governance structures to guide quality planning, execution, monitoring, control, and improvement efforts effectively.

Data Science Use Cases:

- Predictive Analytics for Program Planning
- Automated Scheduling and Resource Allocation
- Risk Prediction and Mitigation
- Workflow Optimization through Process Mining
- Natural Language Processing for Documentation Management

Product Design and Development:

Product design and development encompass conceptualizing, designing, prototyping, testing, validating, refining, finalizing, and documenting product specifications, requirements, architectures, components, interfaces, functionalities, features, attributes, performance metrics, and user experiences to ensure quality, reliability, usability, and satisfaction.

Data Science use cases:

- Predictive Modeling for Product Performance
- Sentiment Analysis of User Feedback
- Design Optimization Algorithms
- Failure Mode and Effects Analysis (FMEA) Automation

- Simulation and Modeling for Prototype Testing

Perform Product and Process Validation:

Performing product and process validation includes conducting comprehensive tests, inspections, audits, evaluations, assessments, verifications, validations, certifications, and approvals to ensure that products and processes meet quality, performance, reliability, safety, compliance, and customer satisfaction criteria.

Data Science use cases:

- Predictive modeling for product failure analysis
- Anomaly detection in manufacturing processes
- Quality control through image recognition
- Statistical analysis for process optimization
- Predictive maintenance for equipment reliability

Manage Production Launch, Assessment, and Improvement:

Managing production launch, assessment, and improvement entails coordinating, monitoring, evaluating, controlling, and optimizing production activities, resources, schedules, costs, risks, performance metrics, quality standards, supplier relationships, customer feedback, and continuous improvement initiatives throughout the product lifecycle.

Data Science use cases:

- Predictive maintenance for equipment reliability
- Quality control through anomaly detection
- Supplier risk assessment and management
- Demand forecasting for production scheduling
- Root cause analysis for production issues

Manage Zero / Pilot Series Readiness Validation:

Managing zero/pilot series readiness validation involves preparing, testing, verifying, validating, approving, and launching initial production batches, pilot runs, trial builds, prototypes, pilot series, pre-production units, pilot lines, pilot plants, pilot programs, pilot projects, or pilot studies to ensure quality, scalability, reliability, efficiency, and effectiveness.

Data Science use cases:

- Predictive modeling for identifying potential issues during pilot series.
- Anomaly detection to flag abnormalities in pilot run data.
- Optimization algorithms for resource allocation during pilot runs.
- Simulation modeling for predicting outcomes of different pilot scenarios.
- Natural language processing for analyzing feedback from pilot testing.

Feedback, Assessment, and Correction Action:

Feedback, assessment, and correction action encompass collecting, analyzing, interpreting, prioritizing, resolving, documenting, communicating, and monitoring feedback, assessments, reports, findings, issues, problems, defects, deviations, non-conformities, failures, complaints, recalls, returns, warranties, liabilities, disputes, claims, and corrective/preventive actions to enhance product quality, customer satisfaction, organizational performance, and regulatory compliance.

Data Science use cases:

- Predictive Analytics for Quality Defects
- Sentiment Analysis of Customer Feedback
- Root Cause Analysis with Machine Learning
- Anomaly Detection for Early Issue Identification
- Predictive Maintenance for Proactive Quality Management

In summary, integrating data science into Advanced Product Quality Planning enhances agility, fosters collaboration, drives innovation, ensures compliance, and maximizes value across the organization. By leveraging advanced analytics, artificial intelligence, automation technologies, and predictive modeling, organizations can navigate complexities, capitalize on opportunities, mitigate risks, and achieve strategic objectives effectively while enhancing stakeholder satisfaction, trust, and loyalty (Cai-yan & You-fa, 2009; Chiliban et al., 2013; Kano et al., 2005; Kenett et al., 2018; Shabani-Naeeni & Ghasemy, 2021; Sun et al., 2021; Wang et al., 2007).

4.1.1.12 Failure Mode and Effects Analysis

Failure Mode and Effects Analysis (FMEA) is a systematic, proactive method for evaluating a process to identify where and how it might fail and to assess the relative impact of different failures, enabling organizations to prioritize and implement effective preventive and corrective actions. This section explores the various sub-functions associated with FMEA and elucidates the potential applications of data science to enhance its efficacy and efficiency.

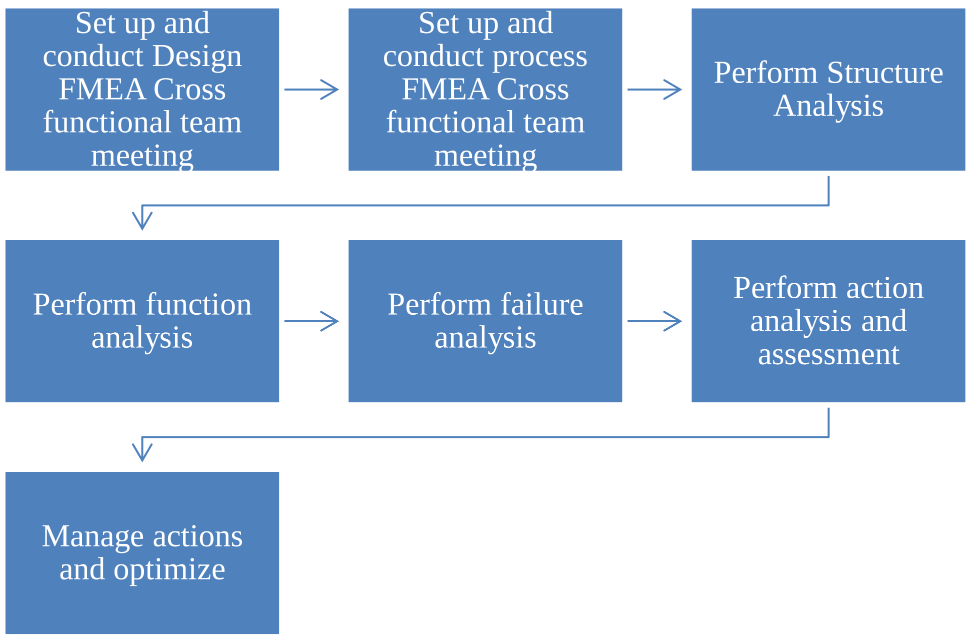

Figure 13 Typical Failure Mode and Effect analysis process flow. Source: Author

Set up and Conduct Design FMEA Cross-Functional Team Meeting:
Organizing and conducting Design FMEA cross-functional team meetings involve assembling multidisciplinary teams comprising experts from design, engineering, manufacturing, quality assurance, supply chain, customer support, and other relevant departments to collaboratively analyze, evaluate, prioritize, and mitigate potential failure modes, causes, effects, risks, and actions related to product design.

Data Science use cases:

- Natural Language Processing (NLP) for meeting transcription and summarization
- Topic modeling to identify common themes and patterns in failure modes.
- Sentiment analysis to gauge team member opinions and concerns
- Network analysis to visualize and analyze communication patterns within the team.
- Time series analysis to track changes and trends in identified failure modes over time.

Set up and Conduct Process FMEA Cross-Functional Team Meeting:

Establishing and conducting Process FMEA cross-functional team meetings entail bringing together cross-functional teams to systematically analyze, assess, address, and improve process-related failure modes, root causes, effects, risks, controls, actions, and outcomes across various stages of product development, production, delivery, service, and disposal.

Data Science use cases:

- Natural Language Processing (NLP) for extracting insights from meeting transcripts
- Network analysis to identify communication patterns within cross-functional teams.
- Time-series analysis to track the effectiveness of actions taken post-meeting.
- Clustering techniques to identify common themes across different process FMEA sessions.
- Visualization techniques to represent FMEA findings and prioritize actions.

Perform Structure Analysis:

Performing structure analysis involves evaluating the structural integrity, reliability, durability, functionality, compatibility, interoperability, safety, compliance, sustainability, and performance of products, components, assemblies, systems, processes, and operations to identify potential failure modes, mechanisms, patterns, trends, correlations, dependencies, and interactions.

Data Science use cases:

- Predictive modeling for identifying potential failure modes.

- Machine learning for detecting patterns and trends in failure data.
- Predictive analytics for forecasting failure probabilities
- Data mining for uncovering correlations and dependencies among variables
- Simulation modeling for assessing the impact of failure scenarios.
- Anomaly detection for identifying unusual behavior indicative of potential failures.

Perform Function Analysis:

Conducting function analysis entails examining the functional requirements, specifications, parameters, constraints, dependencies, interfaces, interactions, interrelationships, and interdependencies of products, components, assemblies, systems, processes, and operations to identify potential failure modes, effects, causes, risks, controls, and actions that may impact performance, quality, reliability, safety, compliance, and customer satisfaction.

Data Science use cases:

- Predictive modeling for identifying potential failure modes based on historical data
- Natural Language Processing (NLP) for analyzing textual descriptions of functions and failure modes.
- Machine learning for automating the identification of dependencies and interactions.
- Clustering algorithms for grouping similar functions and failure modes.
- Anomaly detection techniques for identifying unexpected patterns in function analysis data.

Perform Failure Analysis:

Performing failure analysis involves investigating, diagnosing, classifying, categorizing, prioritizing, quantifying, qualifying, modeling, simulating, predicting, and validating failure modes, causes, effects, mechanisms, patterns, trends, correlations, dependencies, and interactions to understand the underlying root causes, contributing factors, failure mechanisms, failure rates, failure distributions, failure modes, failure effects, and failure impacts.

Data Science use cases:

- Failure mode prediction using machine learning algorithms.
- Failure mode classification using natural language processing.
- Failure trend analysis using time series analysis.
- Failure correlation analysis using statistical modeling.
- Failure simulation using Monte Carlo simulations.
- Failure cause identification using root cause analysis algorithms.
- Failure impact quantification using regression analysis.
- Failure rate modeling using survival analysis techniques.

Perform Action Analysis and Assessment:

Performing action analysis and assessment entails identifying, evaluating, selecting, prioritizing, planning, implementing, monitoring, controlling, reviewing, optimizing, and improving preventive and corrective actions, controls, measures, strategies, tactics, interventions, solutions, recommendations, and initiatives to mitigate risks, resolve issues, address challenges, capitalize on opportunities, and achieve objectives effectively.

Data Science use cases:

- Predictive analytics for identifying potential failure modes.
- Machine learning for prioritizing preventive and corrective actions
- Natural language processing for analyzing historical action effectiveness.
- Optimization algorithms for resource allocation in action planning
- Sentiment analysis for monitoring stakeholder feedback on implemented actions.

Manage Actions and Optimize:

Managing actions and optimizing involve coordinating, communicating, collaborating, monitoring, evaluating, updating, optimizing, and aligning preventive and corrective actions, controls, measures, strategies, tactics, interventions, solutions, recommendations, and initiatives across the organization to ensure alignment with organizational goals, priorities, values, principles, policies, procedures, standards, guidelines, benchmarks, regulations, and requirements.

Data Science use cases:

- Predictive maintenance models for identifying potential failure modes in advance.
- Machine learning algorithms for optimizing preventive and corrective action strategies.
- Natural language processing for analyzing textual data and identifying patterns in action reports.
- Predictive analytics for forecasting the impact of different failure modes and prioritizing actions.
- Network analysis for identifying dependencies between failure modes and optimizing action plans.

In summary, integrating data science into Failure Mode and Effects Analysis enhances agility, fosters collaboration, drives innovation, ensures compliance, and maximizes value across the organization. By leveraging advanced analytics, artificial intelligence, automation technologies, and predictive modeling, organizations can navigate complexities, capitalize on opportunities, mitigate risks, and achieve strategic objectives effectively while enhancing stakeholder satisfaction, trust, and loyalty (Basole et al., 2019; Bian et al., 2018; Braaksma et al., 2012; Chin et al., 2009; Davis et al., 2008).

4.1.1.13 Audit Management

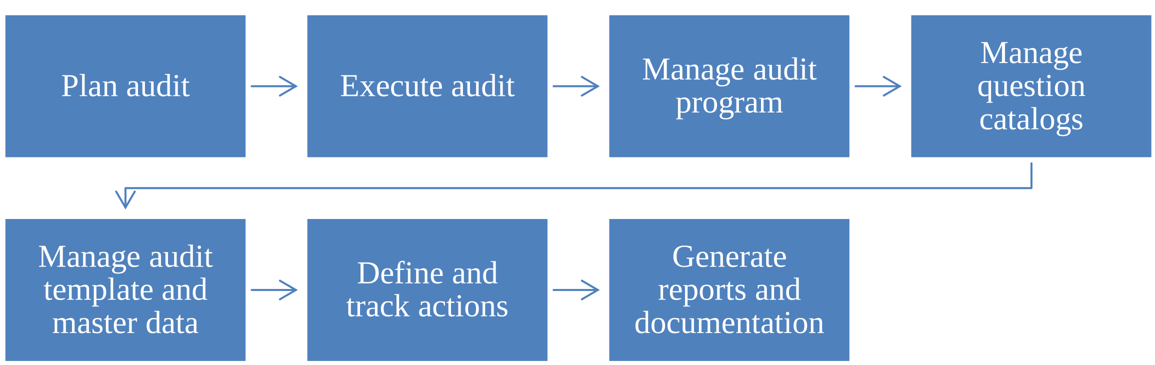

Figure 14 Typical process flow of audit management in product design function.

Source: Author

Audit Management is a critical component of ensuring adherence to standards, policies, regulations, and best practices within an organization. This section delves into the various sub-functions shown in *Figure 15* associated with Audit Management and explores how data science can enhance its effectiveness, efficiency, and adaptability.

Plan Audit: The planning phase involves defining the scope, objectives, criteria, and resources for an audit. It also includes identifying audit risks, priorities, schedules, and teams.

Execute Audit: The execution phase encompasses conducting the actual audit, gathering evidence, interviewing relevant personnel, and assessing compliance with established standards and requirements.

Manage Audit Program: Managing the audit program involves coordinating multiple audits, ensuring consistency in processes, assigning resources, and aligning audit activities with organizational goals.

Manage Question Catalogs: This sub-function involves creating and maintaining catalogs of audit questions, checklists, and criteria used to evaluate processes, systems, and compliance.

Manage Audit Template and Master Data: Audit templates and master data management involve defining standardized formats, templates, and protocols for conducting audits, ensuring consistency and comparability across different audit processes.

Define and Track Actions: Defining and tracking actions refers to identifying corrective and preventive actions based on audit findings and monitoring the implementation and effectiveness of these actions over time.

Generate Reports and Documentation: Creating comprehensive reports and documentation involves summarizing audit findings, outlining recommendations, and providing stakeholders with clear, actionable insights.

Data Science use cases:

- Predictive Analytics for Audit Planning
- Natural Language Processing for Evidence Analysis
- Resource Optimization through Machine Learning
- Automated Question Catalog Maintenance
- Data-driven Audit Template Optimization
- Predictive Modeling for Action Effectiveness
- Automated Report Generation

In summary, integrating data science into Audit Management enhances the overall effectiveness of audit processes. By improving behavioral and situational awareness, enabling inclusive and augmented decision-making, and creating dynamic processes and resource allocation, organizations can conduct audits that are not only compliant but also agile, responsive, and value-driven (Chu & Yong, 2021; Glick, 1992; Jones et al., 2008; Rosnidah et al., 2022; Zhu & Huang, 2019).

4.1.1.14 Substance Compliance & Sustainability Management

Substance Compliance & Sustainability Management is crucial for organizations aiming to meet regulatory requirements, minimize environmental impact, and enhance sustainability practices. This section explores the various sub-functions associated with Substance Compliance & Sustainability Management and examines the role of data science in optimizing these processes.

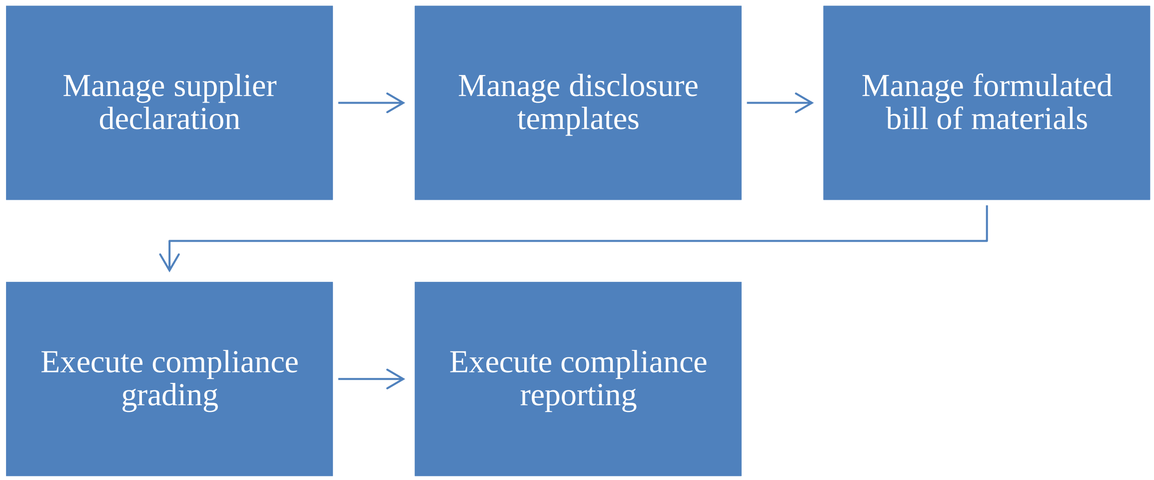

Figure 16 Typical substance compliance and sustainability management process flow. Source: Author

Manage Supplier Declaration:

Managing supplier declarations involves collecting, validating, and monitoring information related to the composition, origin, and compliance of materials supplied by external vendors. This ensures that materials meet regulatory requirements and organizational sustainability goals.

Manage Disclosure Templates:

Managing disclosure templates entails creating standardized formats and protocols for reporting substance compliance and sustainability data. These templates facilitate consistent data collection, analysis, and reporting across different departments, projects, and stakeholders.

Manage Formulated Bill of Materials:

The management of a formulated bill of materials involves documenting and analyzing the composition of products, materials, and components to ensure compliance with substance regulations and sustainability criteria.

Execute Compliance Grading:

Executing compliance grading refers to assessing and categorizing substances, materials, products, and suppliers based on their compliance with regulatory requirements and sustainability standards. This grading system helps prioritize actions, resources, and initiatives to address areas of high risk or non-compliance.

Execute Compliance Reporting:

Executing compliance reporting involves generating comprehensive reports, dashboards, and insights related to substance compliance and sustainability performance. These reports enable stakeholders to monitor progress, identify trends, and make informed decisions regarding compliance strategies and sustainability initiatives.

Data Science use cases:

- Predictive Analytics for Supplier Compliance
- Natural Language Processing for Template Standardization
- Data Mining for Bill of Materials Analysis
- Machine Learning for Compliance Grading
- Data Visualization for Compliance Reporting
- Text Classification for Supplier Declaration Management
- Time Series Analysis for Trend Identification in Sustainability Data
- Cluster Analysis for Supplier Segmentation based on Compliance Levels
- Anomaly Detection for Early Warning of Non-Compliance
- Predictive Modeling for Future Sustainability Performance

In summary, integrating data science into Substance Compliance & Sustainability Management enhances the organization's ability to meet regulatory requirements, minimize environmental impact, and drive sustainable growth. By improving behavioral and situational awareness, enabling inclusive and augmented decision-making, and creating dynamic processes and resource allocation, organizations can navigate the complexities of substance compliance and sustainability with confidence and efficiency (Akkucuk, 2019;

Balaprakash & Dunn, 2021; Egirani & Shehata, 2021; Eugene et al., 2017; Everard, 2023; Tsaples et al., 2022).

4.1.1.15 Environmental, Health & Safety (EHS)

Environmental, Health & Safety (EHS) management is paramount for organizations to ensure a safe and compliant workplace, minimize environmental impact, and protect the health and well-being of employees, stakeholders, and the community. This section delves into the various sub-functions as shown in *Figure 17* associated with EHS management and explores the transformative potential of data science in enhancing these critical processes.

Analyze Aspect and Hazards:

Analyzing aspects and hazards involves identifying, evaluating, and prioritizing potential risks, environmental impacts, and health hazards within organizational operations, processes, and facilities. This assessment forms the basis for developing proactive measures, controls, and mitigation strategies to prevent incidents and ensure compliance with regulatory requirements.

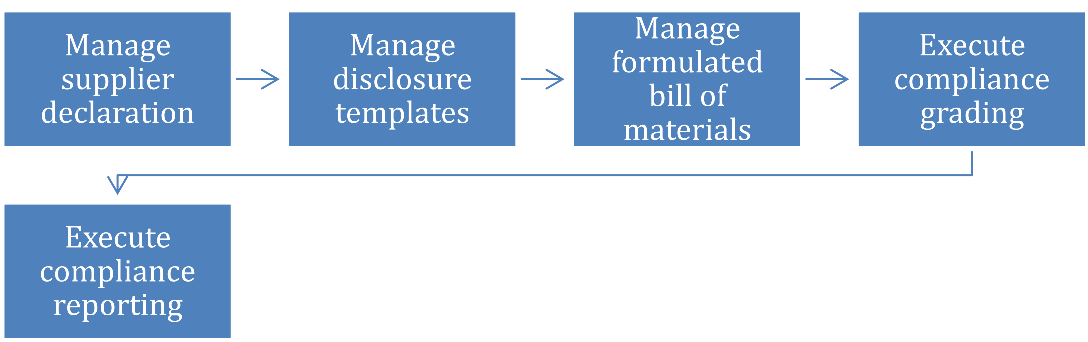

Figure 18 Typical environmental, health and safety process flow. Source: Author

Perform Contingency Planning:

Performing contingency planning entails developing and implementing strategies, protocols, and procedures to address emergencies, incidents, and unexpected events effectively. This includes preparing response plans, mobilizing resources, and coordinating actions to minimize disruptions, mitigate risks, and safeguard personnel, assets, and the environment.

Create Incident Reports:

Creating incident reports involves documenting and investigating incidents, accidents, near misses, and non-compliance events to identify root causes, lessons learned, and opportunities for improvement. This information enables organizations to implement corrective actions, enhance safety protocols, and prevent recurrence of similar incidents in the future.

Identify Aspects and Hazards Register:

Maintaining an aspects and hazards register involves systematically cataloging, tracking, and updating information related to environmental aspects, health hazards, safety risks, and regulatory requirements. This register serves as a central repository for critical EHS data, facilitating informed decision-making, compliance monitoring, and continuous improvement initiatives.

Track Regulations and Permits:

Tracking regulations and permits entails monitoring, interpreting, and ensuring compliance with applicable EHS laws, regulations, standards, and permits. This includes staying abreast of regulatory changes, obtaining necessary permits, renewing licenses, and maintaining documentation to demonstrate compliance with legal requirements.

Perform Safety Data Sheet Tracking:

Performing safety data sheet (SDS) tracking involves managing, updating, and disseminating SDSs for hazardous materials, chemicals, and substances used, stored, or generated within the organization. This ensures that employees, contractors, and stakeholders have access to accurate, up-to-date information regarding potential risks, handling procedures, and emergency response measures.

Perform Control Testing:

Performing control testing entails evaluating the effectiveness, reliability, and integrity of EHS controls, safeguards, and monitoring systems implemented to manage risks, prevent incidents, and ensure compliance. This involves conducting periodic inspections, audits, assessments, and tests to verify adherence to established standards, protocols, and best practices.

Data Science use cases:

- Predictive modeling for identifying potential risks and hazards.
- Optimization algorithms for developing efficient contingency plans.
- Natural Language Processing (NLP) for automating incident report generation
- Machine Learning for automatic updating and classification of aspects and hazards register
- Regulatory compliance prediction models
- Text mining and NLP for automating safety data sheet tracking
- Predictive analytics for identifying control testing priorities.
- Anomaly detection algorithms for identifying deviations in control testing results.
- Time-series analysis for trend detection in regulatory changes
- Image recognition for safety equipment inspection and testing
- Predictive maintenance models for ensuring the reliability of EHS controls.
- Network analysis for assessing the interconnectedness of EHS factors.
- Simulation modeling for evaluating the effectiveness of contingency plans.
- Sentiment analysis for gauging employee perceptions of safety measures
- Predictive analytics for identifying potential incident hotspots.

In summary, integrating data science into Environmental, Health & Safety (EHS) management enhances organizational resilience, regulatory compliance, and stakeholder trust. By improving behavioral and situational awareness, enabling inclusive and augmented decision-making, and creating dynamic processes and resource allocation, organizations can effectively navigate the complexities of EHS management with confidence, efficiency, and effectiveness (Choirat et al., 2019; Gupta et al., 2021; Heacock et al., 2022; Rodrigues & Carfagna, 2023; Viqueira et al., 2020).

4.1.1.16 Mitigation Strategies for Challenges in Adoption of Data Science in PLM, Collaboration, Quality and Governance Function

In the evolving landscape of Product Life Cycle Management (PLM), collaboration, quality, and governance stand as pillars that ensure the seamless progression of a product from conception to retirement. Harnessing the capabilities of data science within this function amplifies efficiency, facilitates informed decision-making, and drives continuous improvement across various business processes. In summary, integrating data science within Product Life Cycle Management collaboration, quality, and governance functions empowers organizations to harness data-driven insights, automation, and predictive analytics. By fostering collaboration, enhancing quality, ensuring governance, and driving continuous improvement, data science serves as a catalyst for innovation, efficiency, and excellence in the dynamic landscape of product development and management. Let's consolidate the challenges the organization may encounter while adopting these data science use cases and discuss on the strategies they can adopt to mitigate those challenges.

Table 1 Data Science Use Cases, Challenges & Mitigation Strategies in Product Life Cycle Management: Collaboration, Quality, and Governance function. Source: Author

Process	**Data Science Use Cases**	**Business Agility Goals**	**Challenges Encountered**	**Mitigation Strategy**
Program Management	Predictive analytics for resource allocation	Create dynamic processes for fast execution	Lack of skilled workforce	Invest in training programs, collaborate with academic institutions
Standards, Global	Machine learning for	Enable augmented	Data quality and availability	Implement data cleansing

Table 1 Data Science Use Cases, Challenges & Mitigation Strategies in Product Life Cycle Management: Collaboration, Quality, and Governance function. Source: Author				
Process	**Data Science Use Cases**	**Business Agility Goals**	**Challenges Encountered**	**Mitigation Strategy**
Attributes & Parameter Management	automated validation	decision making		processes, invest in data governance
Content and Document Management	Natural Language Processing for content categorization	Improve Behavioral Awareness	Integration with existing systems	Adopt interoperable platforms, API integration
Change & Release Management	Predictive modeling for risk assessment	Create dynamic resources for fast execution	Privacy and security concerns	Implement robust encryption, compliance with data protection laws
Issue Management & CAPA	Advanced analytics for root cause analysis	Enable Inclusive decision making	Scalability	Adopt scalable cloud platforms, optimize data storage solutions
Product & Portfolio Management	Predictive analytics for market trend analysis	Improve Situational Awareness	Alignment with business objectives	Establish clear alignment metrics, engage stakeholders
Product Line Variability	Optimization algorithms for personalized	Enable augmented decision making	Lack of standardization	Develop standardized protocols,

Table 1 Data Science Use Cases, Challenges & Mitigation Strategies in Product Life Cycle Management: Collaboration, Quality, and Governance function. Source: Author				
Process	**Data Science Use Cases**	**Business Agility Goals**	**Challenges Encountered**	**Mitigation Strategy**
	product configurations			collaborate with industry bodies
Intellectual Property Management	Machine learning for IP valuation	Improve Behavioral Awareness	Lack of skilled workforce	Partner with specialized agencies, leverage external expertise
Partner & Customer Collaboration	Predictive modeling for customer engagement	Enable Inclusive decision making	Data quality and availability	Implement data validation mechanisms, engage with data providers
Product Cost Management	Advanced analytics for cost-saving opportunities	Create dynamic processes for fast execution	Integration with existing systems	Develop integration APIs, modularize implementation
Advanced Product Quality Planning	Predictive analytics for quality assurance	Improve Situational Awareness	Privacy and security concerns	Implement access controls, audit trails
Failure Mode and Effects Analysis	Machine learning for identifying failure modes	Enable augmented decision making	Scalability	Optimize algorithm efficiency, adopt

Table 1 Data Science Use Cases, Challenges & Mitigation Strategies in Product Life Cycle Management: Collaboration, Quality, and Governance function. Source: Author				
Process	**Data Science Use Cases**	**Business Agility Goals**	**Challenges Encountered**	**Mitigation Strategy**
				distributed computing
Audit Management	Advanced analytics for compliance monitoring	Improve Behavioral Awareness	Alignment with business objectives	Establish audit guidelines, periodic reviews
Substance Compliance & Sustainability Management	Predictive modeling for regulatory compliance	Enable Inclusive decision making	Lack of standardization	Adopt industry standards, collaborate with regulatory bodies
Environmental, Health & Safety (EHS)	Predictive analytics for hazard identification	Improve Situational Awareness	Data quality and availability	Implement sensor networks, real-time monitoring

The above *Table 1* serves as a comprehensive guide that highlights critical challenges within the domain of Product Life Cycle Management (PLM), specifically focusing on collaboration, quality, and governance functions. By identifying these challenges, I can better anticipate associated risks and devise effective mitigation strategies to navigate potential pitfalls. In summary, the *Table 1*underscores the importance of addressing key challenges in PLM collaboration, quality, and governance functions by identifying associated risks and implementing targeted mitigation strategies. By embracing AI-driven analytics, fostering collaboration, and optimizing processes and resources, organizations can enhance agility, resilience, and competitiveness in today's dynamic business environment (Fasoli et al., 2011; Ford et al., 2013; Fukushige et al., 2017; Gambini et al., 2011; Gerhard, 2017; Hayat & Winkler, 2022; Hewett, 2010; Riesener et al., 2019; Zhang et al., 2017).

4.1.2 Mitigation Strategies for Challenges in Adoption of Data Science in Supply Chain Collaboration and Material Management

In a typical Supply Chain Collaboration and Material Management function, various broad business processes play integral roles in ensuring the efficiency and effectiveness of the overall supply chain. These processes encompass the end-to-end journey of materials and products within the supply chain, involving interactions with suppliers, managing incoming goods, ensuring quality standards, and handling customer orders. The key business processes include Supplier Sourcing & Vendor Management, Incoming Goods & Supplier Quality Management, Part Management, Material Management, Bid & Customer Order Management, and Supplier Design Collaboration. Each process contributes to the seamless flow of materials, the maintenance of quality standards, and the facilitation of collaborative relationships with suppliers and customers. Together, these processes form a critical foundation for optimizing the supply chain, enhancing material flow, and meeting customer demands in a streamlined and efficient manner. These broad business processes collectively shape the intricate landscape of Supply Chain Collaboration and Material Management, ensuring a cohesive and responsive approach to the challenges and opportunities within the supply chain.

In summary, these interconnected business processes collectively form the backbone of Supply Chain Collaboration and Material Management. They enable organizations to navigate the complexities of sourcing, production, and delivery, fostering effective collaboration with both suppliers and customers to achieve optimal supply chain performance (Alshahrani, 2023; Amadori et al., 2020; Arias et al., 2022; Barzizza et al., 2023; Dalmarco & Barros, 2018; El Baz et al., 2023; Kuo et al., 2021).

In the following section, I will discuss in detail about each process and list down the different data science cases that can be orchestrated.

4.1.2.1 Supplier sourcing & Vendor Management

Effective supply chain and material management begins with a comprehensive approach to vendor management. This entails a sequence of crucial steps that span the entire vendor relationship lifecycle. Firstly, managing vendors involves establishing strong connections and overseeing their activities to ensure seamless collaboration. Concurrently, the management of vendor parts is vital for optimizing inventory and production processes, guaranteeing the availability of essential components. Supplier qualification management further enhances this process, ensuring that only qualified and reliable partners are engaged. In the commercial realm, meticulous management of commercial parts streamlines operations and enhances efficiency. The process culminates with the awarding of bids, a pivotal decision that hinges on a judicious evaluation of vendor offerings. Subsequently, the preparation and execution of a robust vendor development plan becomes imperative, facilitating continuous improvement and growth within the vendor ecosystem. This holistic approach as shown in *Figure 19* to vendor management serves as the cornerstone of a resilient and streamlined supply chain, fostering sustained success.

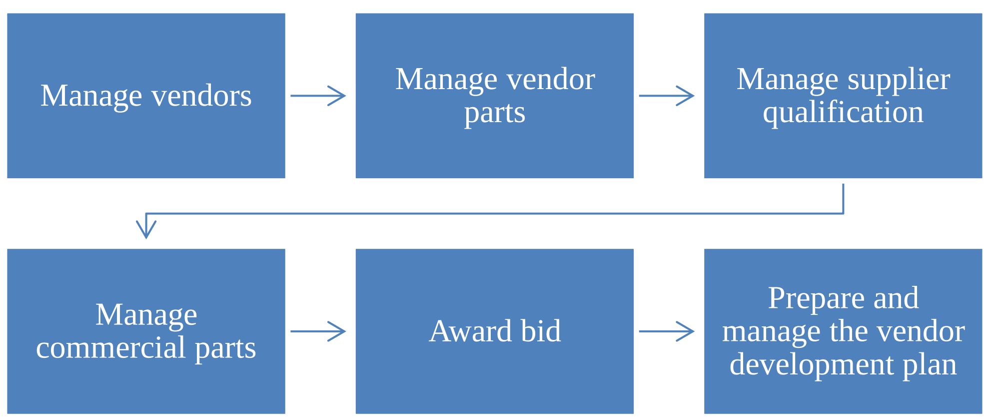

Figure 20 Typical supplier sourcing and vendor management process flow.

Source: Author

Managing Vendors: The first sub-function involves the ongoing management of relationships with vendors. This includes communication, performance monitoring, and issue resolution. Effective vendor management ensures a collaborative and efficient partnership, promoting transparency and trust between the buyer and supplier.

Manage Vendor Parts: This sub-function focuses on the meticulous oversight of individual parts supplied by vendors. It involves cataloging, tracking, and maintaining accurate records of vendor-provided components. Timely and accurate management of vendor parts is crucial for maintaining optimal inventory levels and ensuring a smooth production process.

Manage Supplier Qualification: Supplier qualification is a critical aspect of mitigating risks and ensuring that vendors meet specific standards. This sub-function involves evaluating and documenting a supplier's capabilities, reliability, and adherence to quality standards. A robust qualification process helps in selecting suppliers who align with the organization's strategic goals.

Manage Commercial Parts: Handling the procurement and management of commercial parts is another crucial sub-function. This involves sourcing components or materials that are not produced in-house but are essential for the final product. Effective management of commercial parts ensures a diversified and reliable supply chain.

Award Bid: Awarding bids involves the formal selection of suppliers for specific projects or contracts. This sub-function considers factors such as pricing, delivery timelines, and the overall value offered by potential suppliers. Efficient bid award processes contribute to cost-effectiveness and high-quality outcomes.

Data Science use cases:

- Predictive analytics for vendor performance monitoring
- Inventory optimization using machine learning algorithms
- Supplier risk assessment and prediction models
- Predictive maintenance for vendor-provided equipment
- Natural language processing for bid analysis and vendor communication
- Sentiment analysis for vendor relationship management
- Predictive modeling for demand forecasting of vendor parts
- Anomaly detection for identifying irregularities in vendor-provided components

- Network analysis for identifying optimal supplier networks
- Text mining for extracting insights from vendor contracts and agreements

Prepare and Manage the Vendor Development Plan: Vendor development plans outline strategies for enhancing collaboration and improving supplier performance over time. This sub-function involves creating, implementing, and monitoring these plans. It includes activities such as training, process improvements, and joint initiatives to drive continuous improvement in the supplier's capabilities.

The integration of data science into Supplier Sourcing and Vendor Management processes offers a multifaceted approach to improving decision-making, mitigating risks, and enhancing overall supply chain performance. From predictive analytics to automated compliance monitoring, data science empowers organizations to navigate the complexities of vendor relationships with agility and intelligence (Fallahpour et al., 2018; Hou & Su, 2006; Kibira et al., 2015; Li & Ngom, 2015; Smith & Rupp, 2013).

4.1.2.2 Incoming Goods & Supplier Quality Management

Effective supply chain operations rely on meticulous Incoming Goods & Supplier Quality Management processes. These processes as shown in *Figure 21* encompass a range of critical steps that ensure the integrity and reliability of incoming goods. At the forefront, managing supplier quality rating involves a comprehensive assessment of suppliers' performance, fostering a culture of excellence and accountability. Concurrently, conducting meticulous first article inspections guarantees that initial deliveries meet stringent quality standards. To guide these endeavors, well-defined inspection plans are established, outlining the specific criteria and methodologies for assessing goods. Acquiring quality data throughout the inspection process provides essential insights into product conformance. This data, alongside robust goods inspections, aids in identifying and addressing defects, facilitating continuous improvement. Analysis of defects and trends further informs decision-making, enabling proactive measures to enhance quality. Central to this process is the management of inspection orders, streamlining procedures and enhancing operational efficiency. Should concerns arise, timely communication and action are facilitated through a system for raising concerns, fostering transparency and collaborative problem-solving. Additionally, adeptly managing disposition decisions ensures that non-conforming goods are appropriately handled. All these efforts are bolstered by the establishment and adherence to supplier sampling rules, which contribute to consistent quality assurance. In harmonizing these comprehensive elements, Incoming Goods & Supplier Quality Management serves as a cornerstone in upholding uncompromised quality and reliability within the supply chain, ultimately driving excellence and customer satisfaction.

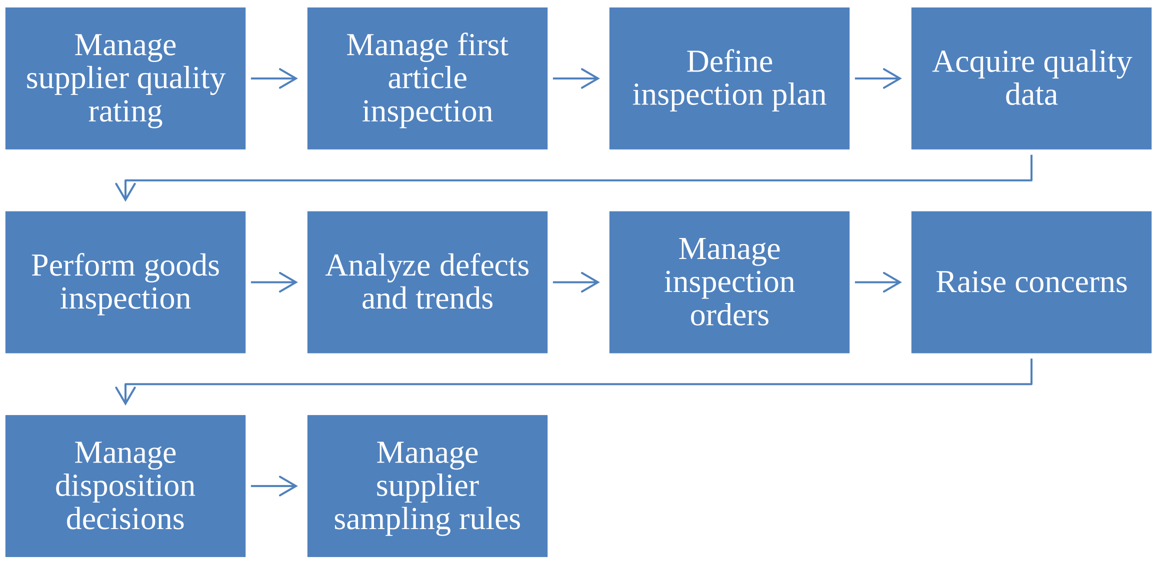

Figure 22 Typical incoming goods and supplier quality management. Source: Author

Manage Supplier Quality Rating: Data science can contribute to the establishment and maintenance of supplier quality ratings by analyzing historical performance data. Algorithms can consider various quality metrics, such as defect rates, delivery accuracy, and adherence to specifications, to generate objective and data-driven quality ratings for each supplier.

Manage First Article Inspection: Data science can streamline the first article inspection process by automating the analysis of initial samples. Machine learning models can learn from past inspections to quickly identify deviations from specifications, ensuring that the first articles meet the required quality standards.

Define Inspection Plan: Data-driven insights can inform the creation of optimized inspection plans. By analyzing historical data on defect types, frequency, and criticality, organizations can tailor inspection plans to focus on high-risk areas, enhancing the overall effectiveness of quality control measures.

Acquire Quality Data: Data science plays a crucial role in acquiring and managing quality data. Automated data collection systems can gather real-time information during the production process, capturing data points related to quality parameters. This data can then be used for analysis and continuous improvement efforts.

Perform Goods Inspection: Automated inspection processes, supported by data science, can enhance the efficiency and accuracy of goods inspection. Computer vision and machine learning algorithms can analyze images and sensor data to quickly identify defects or deviations from quality standards during goods inspection.

Analyze Defects and Trends: Data science enables the analysis of defects and trends by identifying patterns in quality data. Through statistical analysis and machine learning algorithms, organizations can uncover root causes of defects, predict potential quality issues, and implement preventive measures to continuously improve quality.

Manage Inspection Orders: Optimizing inspection orders is facilitated by data science, which can prioritize inspections based on historical defect data, supplier performance, and criticality of the components. This ensures that inspection resources are allocated efficiently to areas with the highest impact on quality.

Raise Concerns: Data-driven early warning systems can automatically raise concerns based on deviations from quality standards. These systems use real-time data to identify anomalies, allowing organizations to address potential issues promptly and prevent the distribution of substandard goods.

Manage Disposition Decisions: Data science aids in disposition decisions by providing insights into the impact of defects on product quality. Decision-making algorithms can recommend appropriate actions, such as rework, rejection, or acceptance, based on historical data and predefined quality criteria.

Manage Supplier Sampling Rules: Data science can optimize supplier sampling rules by analyzing historical data on supplier performance and quality. This ensures that sampling plans are tailored to the specific risk profiles of each supplier, allowing for more targeted quality control efforts.

In the domain of Incoming Goods and Supplier Quality Management, data science plays a pivotal role across various sub-functions to enhance efficiency and ensure high-quality standards. These sub-functions include managing supplier quality ratings, conducting first article inspections, defining inspection plans, acquiring quality data, performing goods inspections, analyzing defects and trends, managing inspection orders, raising concerns, and managing disposition decisions, as well as supplier sampling rules.

Data science contributes to supplier quality ratings by analyzing historical performance data, streamlining first article inspections through automated analysis, and optimizing inspection plans based on historical defect data. It aids in real-time data acquisition, automates goods inspections using computer vision and machine learning, and facilitates the analysis of defects and trends to uncover root causes and predict potential issues.

Furthermore, data-driven early warning systems are employed to raise concerns promptly, while decision-making algorithms assist in managing disposition decisions based on historical data and predefined quality criteria. Supplier sampling rules are optimized by data science, tailoring plans to supplier risk profiles.

The integration of data science elevates the capabilities of Incoming Goods and Supplier Quality Management, fostering proactive decision-making, risk mitigation, and continuous improvement in the overall quality control processes (Eissa & Rashed, 2020; Hazen et al., 2014; Jain et al., 2014; Sajid et al., 2021; West et al., 2021).

4.1.2.3 Part Management

Parts management lies at the heart of efficient supply chain operations, encompassing a series of essential processes as shown in *Figure 23* that contribute to seamless production and product delivery. The management journey begins with the meticulous orchestration of the part introduction process, ensuring a smooth integration of new components into the production ecosystem. This entails defining part usage and meticulously classifying each component, providing a structured framework that streamlines subsequent operations. The pivotal decision of whether to make or buy parts is carefully deliberated, optimizing cost-effectiveness and resource allocation. The foundation of effective parts management rests on the establishment and maintenance of comprehensive part classification libraries, fostering consistency and clarity in categorization. Validation and release processes then follow, wherein parts undergo rigorous scrutiny to guarantee adherence to quality standards before being released for production. Collectively, these processes form a cohesive framework that governs the lifecycle of parts within the supply chain, underpinning operational efficiency and enabling the delivery of high-quality products to customers.

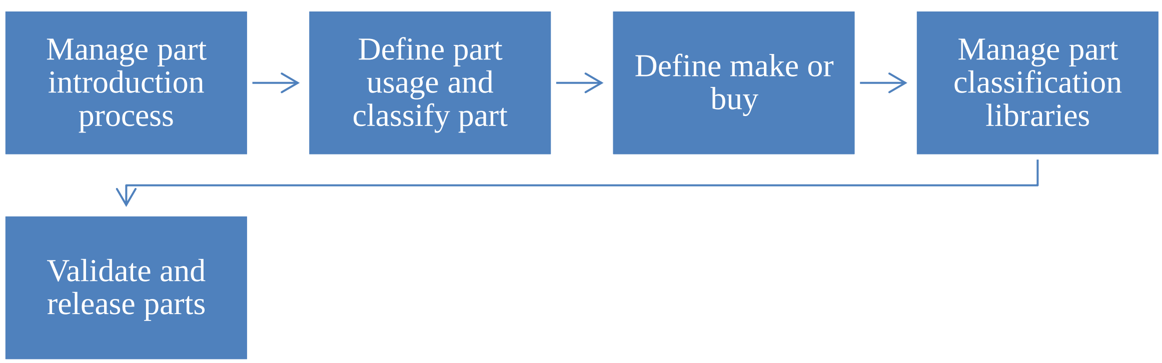

Figure 24 Typical part management process flow. Source: Author

Data science can significantly enhance the "Part Management" activities within the broader scope of Supply Chain Collaboration and Material Management. Below are a few data science uses cases which can be applied to each of the specified activities in a typical part management process.

Manage Part Introduction Process: Data science can analyze historical data to predict potential challenges or delays in the part introduction process. Predictive models can identify patterns, allowing organizations to proactively address issues and optimize the introduction timeline.

Define Part Usage and Classify Part: Data science techniques, such as machine learning classification models, can automate the process of defining part usage and classifying parts. These models can learn from historical usage patterns and characteristics to accurately categorize new parts.

Define Make or Buy: Data science can assist in decision-making by utilizing decision trees and optimization algorithms to evaluate factors influencing the decision to make or buy a part. By analyzing cost structures, lead times, and other relevant data, organizations can make informed decisions aligned with strategic goals.

Manage Part Classification Libraries: Data science can automate the management of part classification libraries through automated data tagging. Natural Language Processing (NLP) algorithms can analyze part descriptions and attributes to consistently classify and tag parts, reducing manual efforts and ensuring accuracy.

Validate and Release Parts: Data science can contribute to part validation by developing quality predictive models. These models can assess the likelihood of a part meeting quality standards based on historical quality data, aiding in the validation process before release.

Real-time Data Integration: Incorporating real-time data feeds into part management systems allows for dynamic adjustments based on current market conditions, supplier performance, or other relevant factors.

Supplier Collaboration Platforms: Implementing data-driven supplier collaboration platforms can enhance communication and information exchange, ensuring that suppliers are involved in the part management process and contributing valuable insights.

Continuous Improvement Analytics: Data science can be employed to conduct continuous improvement analytics on part management processes. By analyzing performance metrics and feedback, organizations can identify areas for enhancement and implement iterative improvements.

Incorporating data science into Part Management activities empowers organizations to make more informed decisions, streamline processes, and proactively address challenges, ultimately contributing to the optimization of Supply Chain Collaboration and Material Management functions (Balazs & Duma, 2012; Feng et al., 2009; Msaaf et al., 2007; Sajid et al., 2021).

4.1.2.4 Material Management

Material management constitutes a vital cornerstone of efficient supply chain orchestration, encompassing a series of essential steps as shown in *Figure 25* that facilitate the seamless flow of resources. At its core, material management begins with the establishment of comprehensive material definitions or specifications, creating a unified framework that guides the handling and utilization of diverse resources. This holistic approach ensures clarity and consistency, promoting effective collaboration across the supply chain. Further enhancing this process is the assignment of shareable materials and the declaration of materials, optimizing resource allocation and fostering a streamlined exchange of components. As the journey unfolds, material analytics and validation take center stage, employing data-driven insights to assess the quality, availability, and suitability of materials. This systematic approach not only enhances decision-making but also upholds the integrity of materials throughout their lifecycle. Collectively, these processes harmonize to create a robust material management system, which is indispensable for achieving operational excellence, mitigating risks, and driving value across the supply chain landscape.

Figure 26 Typical Material management process flow. Source: Author

In the realm of Supply Chain Collaboration and Material Management, the effective utilization of data science is instrumental in optimizing various activities within "Material Management." This section explores how data science can be applied to three key activities: making holistic material definitions or specifications, assigning shareable material, and performing material analytics and validation.

Material Management is a critical aspect of supply chain operations, involving the definition, assignment, and analysis of materials. Leveraging data science in this domain can enhance decision-making, streamline processes, and contribute to overall supply chain efficiency.

Holistic Material Definitions: Data science plays a pivotal role in the creation of comprehensive material definitions or specifications. Natural Language Processing (NLP) algorithms can analyze textual data, extracting relevant information from diverse sources to formulate detailed and accurate material specifications. This data-driven approach ensures a holistic representation of material characteristics, supporting informed decision-making during the supply chain processes.

Assigning Shareable Material: Data science facilitates the assignment of shareable material by developing algorithms that consider compatibility, availability, and usage patterns. Machine learning models can predict optimal material assignments based on historical data, supplier capabilities, and specific project requirements. This approach enhances collaboration by ensuring efficient sharing and utilization of materials across different facets of the supply chain.

Performing Material Analytics and Validation: Data science-driven analytics provide a powerful tool for scrutinizing material-related data. Predictive analytics models can assess the viability of materials in real-time, identifying potential issues before they escalate. This enables proactive decision-making, minimizes risks, and contributes to the validation of materials throughout the supply chain processes.

In conclusion, the integration of data science into Material Management activities offers a data-driven approach to holistic material definitions, shareable material assignments, and robust material analytics. By harnessing NLP, machine learning, and predictive analytics, organizations can enhance the accuracy of material specifications, optimize material assignments, and proactively address challenges in material validation. This data-centric approach ensures a more efficient and collaborative supply chain, ultimately contributing to improved overall material management within the broader context of supply chain collaboration (Blaiszik et al., 2019; Kalidindi, 2015; Kalidindi & De Graef, 2015; Kuo et al., 2021; Li & Hu, 2016; Sajid et al., 2021).

4.1.2.5 Bid Response & Customer Order Management

Bid Response and Customer Order Management form the pivotal nexus of supply chain operations, encompassing a sequence of strategic processes as shown in *Figure 27* that underpin successful customer engagement and satisfaction. The journey commences with the adept management of early customer requirements, capturing the nuanced essence of their needs and aspirations. Subsequently, executing initial engineering for bid response involves a meticulous fusion of technical prowess and innovation, aligning solutions with customer expectations. Complementing this, the execution of work configuration for bid response weaves together intricate details, orchestrating a coherent and compelling proposal. Central to this process is the careful definition of the bid itself, encapsulating comprehensive insights that resonate with customer objectives.

Steering forward, a well-structured response process is meticulously managed, harnessing the collective expertise of cross-functional teams to craft a robust bid. This phase ensures seamless communication, collaboration, and alignment with customer requirements. Validation and finalization then come to the fore, where the bid response is subjected to rigorous scrutiny and refinement. This validation process, infused with analytical rigor, safeguards precision and quality.

In essence, Bid Response and Customer Order Management epitomize the art of harmonizing customer aspirations with operational excellence. By intertwining these intricate processes, organizations can not only deliver value-driven bids but also cultivate enduring partnerships based on trust, innovation, and unparalleled customer experiences.

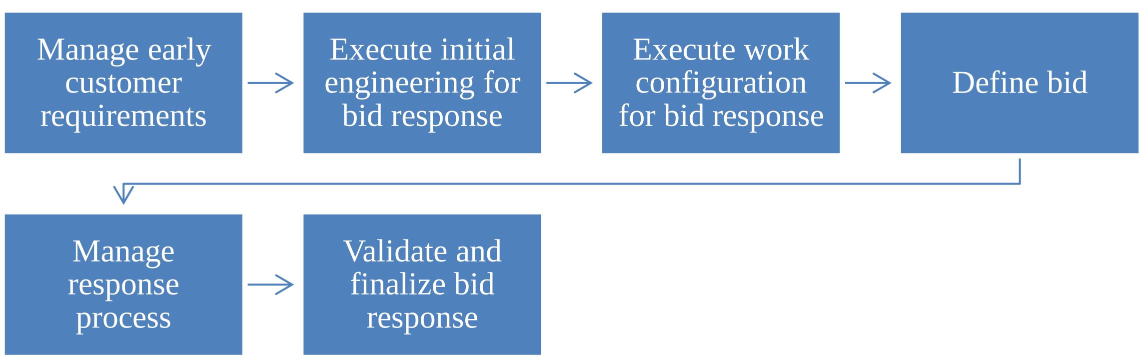

Figure 28 Typical bid response and customer order management process flow.

Source: Author

In the realm of Supply Chain Collaboration and Material Management, the integration of data science into Bid Response & Customer Order Management processes can significantly enhance efficiency and decision-making. This section delves into how data science can be applied to activities related to managing early customer requirements, executing initial engineering for bid response, executing work configuration for bid response, defining bids, managing response processes, and validating and finalizing bid responses.

Data Science in Bid Response & Customer Order Management:

Managing Early Customer Requirements: Data science aids in managing early customer requirements by analyzing historical customer data and preferences. Machine learning models can identify patterns and predict potential requirements based on past interactions, enabling organizations to anticipate customer needs more effectively.

Executing Initial Engineering for Bid Response: Data science contributes to initial engineering processes by optimizing resource allocation and project planning. Predictive analytics models can analyze project parameters, historical engineering data, and resource availability to provide insights into the optimal engineering approach for bid response.

Executing Work Configuration for Bid Response: Machine learning algorithms can be applied to configure work processes efficiently based on historical data. By considering past configurations and their success rates, data science ensures that work configurations for bid responses are tailored to maximize effectiveness and minimize errors.

Defining Bid: Data science plays a crucial role in defining bids by automating the analysis of bid requirements and market conditions. Natural Language Processing (NLP) algorithms can process bid documents, extract relevant information, and recommend optimal bid structures based on historical bid data and success factors.

Managing Response Process: Automated response processes are facilitated by data science, ensuring swift and accurate responses to customer bids. Machine learning models can evaluate response times, customer preferences, and historical success rates to optimize the response process and increase the likelihood of successful bids.

Validating and Finalizing Bid Response: Data science-driven validation processes involve analyzing bid response data for accuracy and completeness. Predictive models can identify potential issues or discrepancies, ensuring that bid responses align with customer requirements and quality standards before finalization.

In summary, the integration of data science into Bid Response & Customer Order Management activities enhances various facets of the supply chain. From anticipating customer requirements and optimizing engineering processes to automating bid configuration and validation, data science ensures a more informed and efficient bid response process. This data-centric approach contributes to improved collaboration and decision-making within the broader context of supply chain and material management (Balazs & Duma, 2012; Boehmke et al., 2020; Delgado et al., 2020; Lu et al., 2021; Pei, 2022; Sajid et al., 2021).

4.1.2.6 Supplier Design Collaboration

Supplier Design Collaboration activity serves as a dynamic nexus of cooperative innovation within the supply chain, orchestrated through a series of well-coordinated processes as shown in *Figure 29*. The journey commences by diligently preparing the context and sending a well-structured request, laying the foundation for collaborative design endeavors. In the subsequent phase, design takes shape within the context, as suppliers harmonize their expertise with the project's requirements. This collaborative synergy ensures that designs are not only innovative but also seamlessly integrated.

The momentum of collaboration persists as suppliers prepare and meticulously submit their responses, reflecting a fusion of ingenuity and practicality. A comprehensive review process ensues, where responses are meticulously evaluated against defined criteria, fostering a culture of continuous improvement. Upon completion, supplier designs are published, catalyzing a dissemination of insights, ideas, and solutions across the ecosystem.

In essence, the Supplier Design Collaboration activity embodies a harmonious interplay of expertise, ingenuity, and cooperation. By adhering to these processes, organizations forge a resilient foundation for co-creation, bolstering innovation, agility, and fostering enduring partnerships within the supply chain landscape.

In the domain of Supply Chain Collaboration and Material Management, the infusion of data science into Supplier Design Collaboration activities holds the potential to enhance collaboration and efficiency. This section explores how data science can be leveraged in activities involving the preparation and sending of requests, designing in context, preparing, and submitting responses, reviewing responses, and publishing supplier designs.

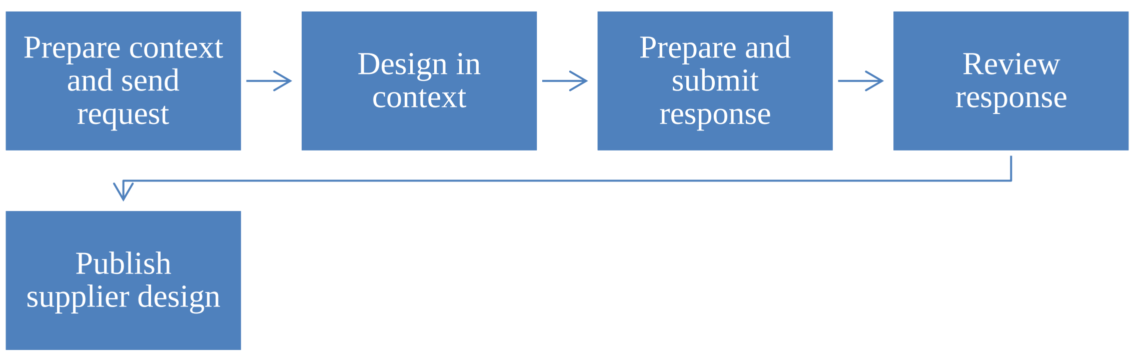

Figure 30 Typical supplier design collaboration process flow. Source: Author

Data Science in Supplier Design Collaboration: Data science facilitates the preparation and sending of requests by analyzing historical data and contextual information. Machine learning algorithms can predict the optimal context for a request, improving the relevance and specificity of collaboration initiatives with suppliers.

Designing in context benefits from data science by incorporating predictive modeling. Machine learning models can analyze design parameters, historical design data, and contextual information to suggest optimal design choices, streamlining the collaborative design process.

The preparation and submission of responses benefit from automated systems driven by data science. Natural Language Processing (NLP) algorithms can process response documents, extract relevant information, and recommend improvements based on historical response data, ensuring completeness and accuracy.

Reviewing responses is enhanced by data science through automated analysis tools. Machine learning models can evaluate response quality, identifying potential issues or areas of improvement. This objective evaluation supports a more informed and efficient review process.

Publishing supplier designs is streamlined through data-driven systems. Predictive analytics models can assess the suitability of designs for publication, considering factors such as compliance, quality, and historical design success. This ensures that published designs meet specified standards and enhance overall collaboration.

In conclusion, the integration of data science into Supplier Design Collaboration activities within the broader context of Supply Chain Collaboration and Material Management brings about improvements in contextual preparation, design optimization, response processing, response review, and design publication. This data-centric approach fosters more effective collaboration, informed decision-making, and streamlined processes throughout the supplier design lifecycle (Feng et al., 2009; Lazarova-Molnar et al., 2019; Wang & Tang, 2007; Yu et al., 2008).

4.1.2.7 Mitigation Strategies for Challenges in Adoption of Data Science

Below table provides a snapshot of which data science use case can be applied in each aspect of the supply chain collaboration and materials management processes, challenges faced and proposed mitigation.

Table 2 Data Science Use Cases for the various process in Supply Chain Collaboration and Material Management Function. Source: Author

Process	**Data Science Use Cases**	**Business Agility Goals**	**Challenges**	**Mitigation Strategies**
Supplier Sourcing & Vendor Management	Predictive analytics for supplier selection	Improve Behavioral Awareness, Enable Inclusive Decision Making	Data privacy and security concerns	Implement robust encryption, compliance with data regulations, regular audits
Supplier Sourcing & Vendor Management	Risk assessment algorithms for vendor management	Enable Augmented Decision Making	Overreliance on AI without human oversight	Establish clear human-AI collaboration protocols, continuous monitoring
Supplier Sourcing & Vendor Management	Automated contract analysis for compliance monitoring	Enable Inclusive Decision Making	Lack of interpretability in AI decisions	Use interpretable models, document decision processes, involve domain experts

Table 2 Data Science Use Cases for the various process in Supply Chain Collaboration and Material Management Function. Source: Author				
Process	**Data Science Use Cases**	**Business Agility Goals**	**Challenges**	**Mitigation Strategies**
Incoming Goods & Supplier Quality Management	Image recognition for product inspection	Improve Situational Awareness, Enable Augmented Decision Making	False positives/negatives in inspections	Regularly update and fine-tune algorithms, conduct frequent calibration
Incoming Goods & Supplier Quality Management	Predictive maintenance for machinery	Improve Situational Awareness, Create Dynamic Resources for Fast Execution	Inaccurate predictions leading to downtime	Incorporate real-time feedback, integrate with traditional maintenance methods
Incoming Goods & Supplier Quality Management	Real-time monitoring for quality control	Improve Situational Awareness, Enable Augmented Decision Making	Technical malfunctions in monitoring tools	Implement redundancy, conduct regular system checks and maintenance
Part Management	Demand forecasting for optimal inventory levels	Create Dynamic Processes for Fast Execution	Inaccurate forecasts leading to overstock/shortages	Implement continuous learning algorithms, incorporate feedback loops

Table 2 Data Science Use Cases for the various process in Supply Chain Collaboration and Material Management Function. Source: Author

Process	**Data Science Use Cases**	**Business Agility Goals**	**Challenges**	**Mitigation Strategies**
Part Management	Identifying alternative sources for part procurement	Enable Inclusive Decision Making	Limited supplier collaboration	Foster transparent communication, incentivize collaboration
Part Management	Predictive analytics for inventory optimization	Create Dynamic Processes for Fast Execution	Data inaccuracies impacting decisions	Regularly clean and update data sources, implement data quality checks
Material Management	Machine learning for accurate demand forecasting	Improve Situational Awareness, Create Dynamic Resources for Fast Execution	Unforeseen market disruptions	Implement scenario planning, maintain flexibility in supply chain
Material Management	Logistics planning and optimization using AI algorithms	Create Dynamic Processes for Fast Execution	Technical glitches in planning algorithms	Conduct rigorous testing, implement fail-safes, have manual backup plans
Material Management	Real-time tracking and monitoring of inventory levels	Improve Situational Awareness	Data inaccuracies impacting tracking	Implement RFID and IoT technologies, conduct regular data audits

Table 2 Data Science Use Cases for the various process in Supply Chain Collaboration and Material Management Function. Source: Author

Process	**Data Science Use Cases**	**Business Agility Goals**	**Challenges**	**Mitigation Strategies**
Bid & Customer Order Management	AI-driven bid management for efficient and accurate bidding	Create Dynamic Processes for Fast Execution	Unintended bias in bidding decisions	Regularly audit and adjust algorithms, involve diverse teams in model development
Bid & Customer Order Management	Order processing automation for faster fulfillment	Create Dynamic Processes for Fast Execution	Technical malfunctions in automation tools	Implement redundancy, conduct regular system checks and maintenance
Bid & Customer Order Management	Predictive analytics for demand sensing in order fulfillment	Create Dynamic Processes for Fast Execution	Inaccurate demand predictions	Implement continuous learning algorithms, incorporate feedback loops
Supplier Design Collaboration	- Real-time collaboration tools for design optimization	Improve Behavioral Awareness, Create Dynamic Processes for Fast Execution	Resistance to adopting new collaboration tools	Provide comprehensive training, address user concerns, offer incentives
Supplier Design Collaboration	- Data sharing platforms for	Improve Behavioral Awareness,	Data security and privacy concerns	Implement encryption, user access controls,

Table 2 Data Science Use Cases for the various process in Supply Chain Collaboration and Material Management Function. Source: Author				
Process	**Data Science Use Cases**	**Business Agility Goals**	**Challenges**	**Mitigation Strategies**
	seamless communication	Enable Inclusive Decision Making		and regular security audits
Supplier Design Collaboration	- AI-driven design analysis for improved collaboration	Enable Inclusive Decision Making, Create Dynamic Processes for Fast Execution	Lack of trust in AI-driven design decisions	Provide transparency on AI decision processes, involve users in model validation

Above *Table 2* delineates a comprehensive overview of Data Science use cases tailored for various processes within Supply Chain Collaboration and Material Management functions along with the associated risks and mitigation strategies. In essence, above *Table 2* serves as a strategic guide, aligning specific Data Science use cases with corresponding business agility goals while highlighting associated risks and recommending mitigation strategies tailored for each process within the supply chain and material management domain.

4.1.3 Mitigation Strategies for Challenges in Adoption of Data Science in Design Simulation and Exploration function

Below would be the broad business processes in a typical function responsible for product life cycle management collaboration, quality, and governance.

1D Multiphysics System Simulation
3D CAE Simulation
CCM & CFD Simulation and Design Impact Prediction
Virtual Product Visualization & Validation

Acoustic Testing & Optimization

Electrical Simulation

Simulation Data Management

In Design Simulation and Exploration function, the integration of data science has emerged as a transformative force, enabling enhanced efficiency, accuracy, and innovation across various business processes. This section delves into the pivotal areas where data science intersects with the traditional functions of design simulation, ushering in a new era of computational modeling and analysis. In conclusion, the symbiotic relationship between data science and design simulation processes is propelling the field towards unprecedented heights of efficiency and innovation. The infusion of data-driven methodologies in each facet of Design Simulation and Exploration outlined above is indicative of a paradigm shift, where computational models are not only accurate but also dynamic, adaptive, and continually refined through iterative learning. This integration holds the promise of revolutionizing how engineering design is conceptualized, simulated, and ultimately brought to fruition (Abdulla et al., 2004; Giunta, 2002; Osman & Mines, 2015; Xie et al., 2018).

4.1.3.1 1D Multiphysics System Simulation

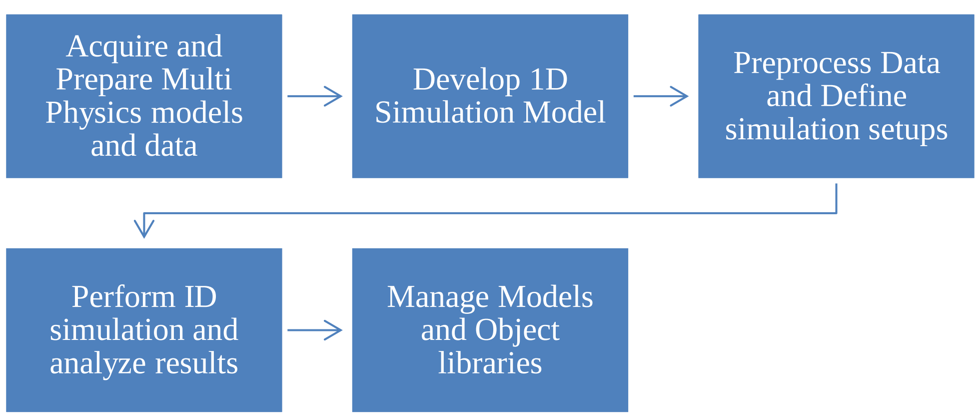

Figure 31 Typical 1 D Multiphysics System Simulation Process Flow. Source: Author

1D (single dimensional) Multiphysics System Simulation stands as a cornerstone in the domain of computational modeling, enabling engineers to simulate complex systems with reduced computational overhead. This section elucidates the sub-functions as shown in *Figure 32* integral to 1D Multiphysics System Simulation and delves into the transformative impact of data science on enhancing its capabilities.

Acquire and Prepare Multi-Physics Models and Data: The initial step in 1D Multiphysics System Simulation involves acquiring and preparing multi-physics models and data. Data science facilitates this process by automating data collection from disparate sources, ensuring data integrity, and standardizing formats for seamless integration into simulation models. Advanced data analytics techniques can preprocess raw data, identify anomalies, and enhance the quality of input parameters, thereby laying a robust foundation for subsequent simulation activities.

Develop 1D Simulation Model: Data science empowers engineers to develop intricate 1D simulation models by leveraging algorithmic approaches, machine learning techniques, and computational algorithms. By analyzing historical simulation data and identifying patterns, data science facilitates the development of predictive models that accurately replicate real-world system behavior, leading to more reliable simulation outcomes.

Preprocess Data and Define Simulation Setups: Preprocessing data and defining simulation setups are pivotal aspects of 1D Multiphysics System Simulation. Data science streamlines this process by automating data cleansing, normalization, and transformation tasks. By employing statistical analysis and machine learning algorithms, data science enables engineers to define optimal simulation setups, ensuring that simulations are conducted under realistic conditions and yield actionable insights.

Perform 1D Simulation and Analyze Results: Performing 1D simulations and analyzing results are critical phases where data science demonstrates its transformative potential. Data-driven approaches facilitate real-time monitoring of simulation parameters, enabling engineers to identify anomalies, optimize model parameters, and refine simulation strategies iteratively. Through advanced analytics and visualization tools, data science empowers engineers to extract meaningful insights from simulation results, fostering a deeper understanding of system behavior and performance.

Manage Models and Object Libraries: Effective management of models and object libraries is essential for ensuring consistency, reusability, and scalability in 1D Multiphysics System Simulation. Data science enhances model management by implementing robust version control systems, metadata repositories, and object libraries. By leveraging data-driven methodologies, engineers can categorize, catalog, and retrieve models efficiently, facilitating collaborative design efforts and accelerating innovation cycles.

In summary, the integration of data science into 1D Multiphysics System Simulation revolutionizes traditional methodologies, enabling engineers to achieve unprecedented levels of efficiency, accuracy, and innovation. By leveraging data-driven approaches across various sub-functions, data science empowers engineers to navigate complexities, optimize design strategies, and accelerate simulation workflows, thereby reshaping the landscape of computational modeling and analysis (Aloisio & Cavaliere, 2009; Glake et al., 2021; Jiao et al., 2006; Keyes et al., 2013; Krol & Zydek, 2013; Michopoulos et al., 2003; Michopoulos et al., 2005).

4.1.3.2 3D CAE Simulation

3D CAE (Computer-Aided Engineering) Simulation stands as a pivotal technique in modern engineering, facilitating the virtual testing and analysis of complex systems. This section elucidates the key sub-functions as shown in *Figure 33* associated with 3D CAE Simulation and explores the transformative impact of data science in elevating its capabilities.

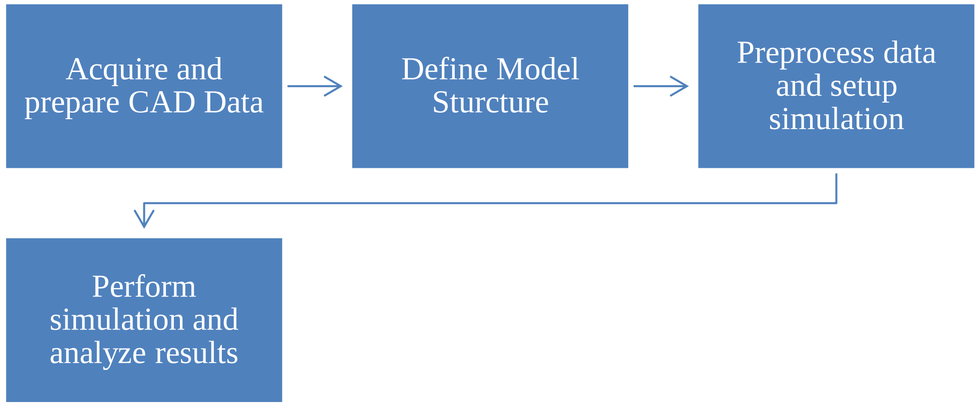

Figure 34 Typical 3D CAE Simulation Process. Source: Author

Acquire and Prepare CAD Data:

The foundation of 3D CAE Simulation lies in acquiring and preparing CAD (Computer-Aided Design) data, which serves as the blueprint for virtual testing. Data science plays a pivotal role in automating CAD data extraction, standardizing formats, and ensuring data integrity. Through advanced data preprocessing techniques, data science facilitates the seamless integration of CAD data into simulation environments, enabling engineers to develop accurate and reliable computational models.

Define Model Structure:

Defining the model structure is a critical phase in 3D CAE Simulation, where engineers delineate the geometric, material, and boundary conditions of the virtual prototype. Data science enhances this process by leveraging algorithmic approaches, machine learning techniques, and optimization algorithms. By analyzing historical simulation data and identifying patterns, data science empowers engineers to define optimal model structures, ensuring that simulations are conducted under realistic conditions and yield actionable insights.

Preprocess Data and Setup Simulation:

Preprocessing data and setting up simulation parameters are fundamental aspects of 3D CAE Simulation. Data science streamlines this process by automating data cleansing, normalization, and transformation tasks. By employing statistical analysis, machine learning algorithms, and computational techniques, data science enables engineers to define optimal simulation setups, ensuring accurate representation of real-world scenarios and facilitating comprehensive analysis.

Perform Simulation and Analyze Results:

Performing simulations and analyzing results constitute the core of 3D CAE Simulation, where engineers assess system performance, identify potential issues, and optimize design parameters. Data science enhances this phase by facilitating real-time monitoring of simulation parameters, enabling engineers to identify anomalies, optimize model parameters, and refine simulation strategies iteratively. Through advanced analytics, visualization tools, and machine learning algorithms, data science empowers engineers to extract meaningful insights from simulation results, fostering a deeper understanding of system behavior and performance.

In conclusion, the integration of data science into 3D CAE Simulation redefines traditional methodologies, enabling engineers to achieve unprecedented levels of efficiency, accuracy, and innovation. By harnessing data-driven approaches across various sub-functions, data science empowers engineers to navigate complexities, optimize design strategies, and accelerate simulation workflows, thereby revolutionizing the landscape of computational engineering and analysis (Ennouri, 2019; Mubaid et al., 2008; Wolski & Narciso, 2017; Xie et al., 2018).

4.1.3.3 CCM & CFD Simulation and Design Impact Prediction

CCM (Computational Continuum Mechanics) and CFD (Computational Fluid Dynamics) simulations, coupled with design impact prediction, form a critical nexus in modern engineering practices. This section provides an in-depth exploration of the sub-functions as shown in *Figure 35* inherent to CCM & CFD Simulation and Design Impact Prediction, elucidating the transformative role of data science in augmenting its capabilities.

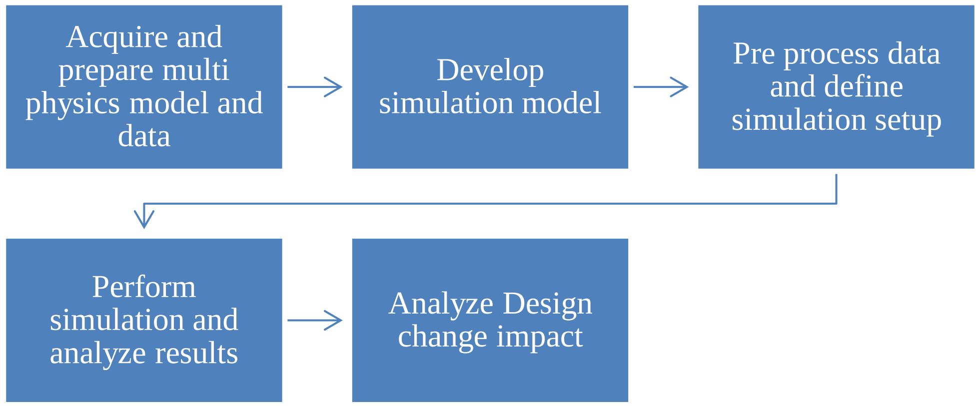

Figure 36 CCM & CFD Simulation and Design Impact Prediction Process Flow. Source: Author

Acquire and Prepare Multi-Physics Model and Data:

The foundational step in CCM & CFD Simulation entails acquiring and preparing multi-physics models and data. Data science plays an instrumental role in automating data extraction from diverse sources, ensuring data integrity, and standardizing formats for seamless integration into simulation frameworks. Through advanced data preprocessing techniques, data science facilitates the harmonization of multi-physics models and datasets, paving the way for accurate and reliable simulations.

Develop Simulation Model:

Developing a robust simulation model forms the bedrock of CCM & CFD Simulation. Data science empowers engineers to construct intricate simulation models by harnessing algorithmic approaches, machine learning techniques, and optimization algorithms. By analyzing historical simulation data and discerning patterns, data science facilitates the creation of predictive models that emulate real-world phenomena with unparalleled fidelity.

Preprocess Data and Define Simulation Setup:

Preprocessing data and defining simulation setups are pivotal facets of CCM & CFD Simulation. Data science streamlines this process by automating data cleansing, normalization, and transformation tasks. By leveraging statistical analysis, machine learning algorithms, and computational methodologies, data science enables engineers to delineate optimal simulation parameters, ensuring comprehensive analysis and actionable insights.

Perform Simulation and Analyze Results:

Executing simulations and analyzing outcomes constitute the crux of CCM & CFD Simulation. Data science enhances this phase by enabling real-time monitoring of simulation parameters, facilitating anomaly detection, and optimizing model parameters iteratively. Through advanced analytics, visualization tools, and machine learning algorithms, data science empowers engineers to extract profound insights from simulation results, fostering a nuanced understanding of system behavior and performance.

Analyze Design Change Impact:

Analyzing the impact of design changes is paramount in CCM & CFD Simulation, enabling engineers to optimize product designs iteratively. Data science facilitates this process by quantifying design modifications' effects, predicting performance alterations, and recommending optimization strategies. By leveraging predictive analytics, simulation data, and machine learning algorithms, data science enables engineers to make informed decisions, mitigate risks, and expedite design optimization cycles.

In summary, the integration of data science into CCM & CFD Simulation and Design Impact Prediction redefines conventional methodologies, enabling engineers to achieve unparalleled levels of accuracy, efficiency, and innovation. By harnessing data-driven approaches across various sub-functions, data science empowers engineers to navigate complexities, optimize design strategies, and accelerate simulation workflows, thereby reshaping the landscape of computational engineering and analysis (Cronemyr et al., 2001; Kabeel et al., 2019; Sajid et al., 2021; Southall et al., 2015).

4.1.3.4 Virtual Product Visualization & Validation

Virtual Product Visualization & Validation stands at the forefront of modern engineering, enabling stakeholders to envision, collaborate, and validate product designs in immersive digital environments. This section delves into the core sub-functions as shown in *Figure 37* integral to Virtual Product Visualization & Validation and elucidates the pivotal role of data science in augmenting its capabilities.

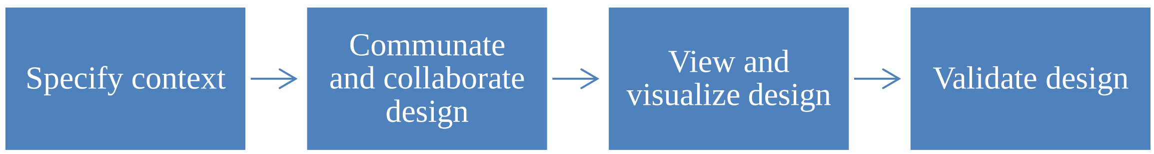

Figure 38 Typical Virtual Product Visualization & Validation. Source: Author

Specify Context: Specifying context forms the foundational step in Virtual Product Visualization & Validation, where engineers and designers delineate the scope, objectives, and constraints of the virtual product design. Data science enhances this process by facilitating contextual analysis, trend identification, and predictive modeling. By leveraging historical data, market insights, and user feedback, data science enables stakeholders to define precise contexts, align design objectives, and optimize product specifications.

Communicate and Collaborate Design: Effective communication and collaboration are paramount in Virtual Product Visualization & Validation, fostering interdisciplinary synergy and innovation. Data science fosters collaboration by implementing collaborative platforms, shared repositories, and interactive visualization tools. By leveraging advanced analytics, machine learning algorithms, and communication frameworks, data science enables stakeholders to exchange ideas, share insights, and co-create designs seamlessly, irrespective of geographical constraints.

View and Visualize Design: Viewing and visualizing designs in immersive, interactive environments constitute the essence of Virtual Product Visualization & Validation. Data science enhances visualization capabilities by implementing augmented reality (AR), virtual reality (VR), and mixed reality (MR) technologies. By leveraging 3D modeling, simulation data, and visualization algorithms, data science enables stakeholders to explore designs, evaluate aesthetics, and assess functionalities in realistic contexts, fostering a deeper understanding and appreciation of product nuances.

Validate Design: Validating design integrity, performance, and compliance is crucial in Virtual Product Visualization & Validation, ensuring product viability and market readiness. Data science facilitates validation by implementing simulation-driven design analysis, predictive modeling, and performance optimization. By leveraging historical data, simulation results, and validation algorithms, data science empowers stakeholders to assess design robustness, identify potential issues, and refine product specifications iteratively, mitigating risks and enhancing product quality.

In summary, the integration of data science into Virtual Product Visualization & Validation redefines conventional methodologies, enabling stakeholders to achieve unparalleled levels of design insight, collaboration, and innovation. By harnessing data-driven approaches across various sub-functions, data science empowers stakeholders to navigate complexities, optimize design strategies, and accelerate product development workflows, thereby reshaping the landscape of virtual product design and validation (Bohm et al., 2005; Bordegoni et al., 2010; Jain et al., 2017; Plant et al., 2021; Srivastav et al., 2009; Žáková et al., 2007).

4.1.3.5 Acoustic Testing & Optimization

Acoustic Testing & Optimization is a critical domain that focuses on assessing, understanding, and enhancing the acoustic properties of products and environments. This section delves into the comprehensive sub-functions as shown in *Figure 39* integral to Acoustic Testing & Optimization and elucidates the transformative role of data science in amplifying its capabilities.

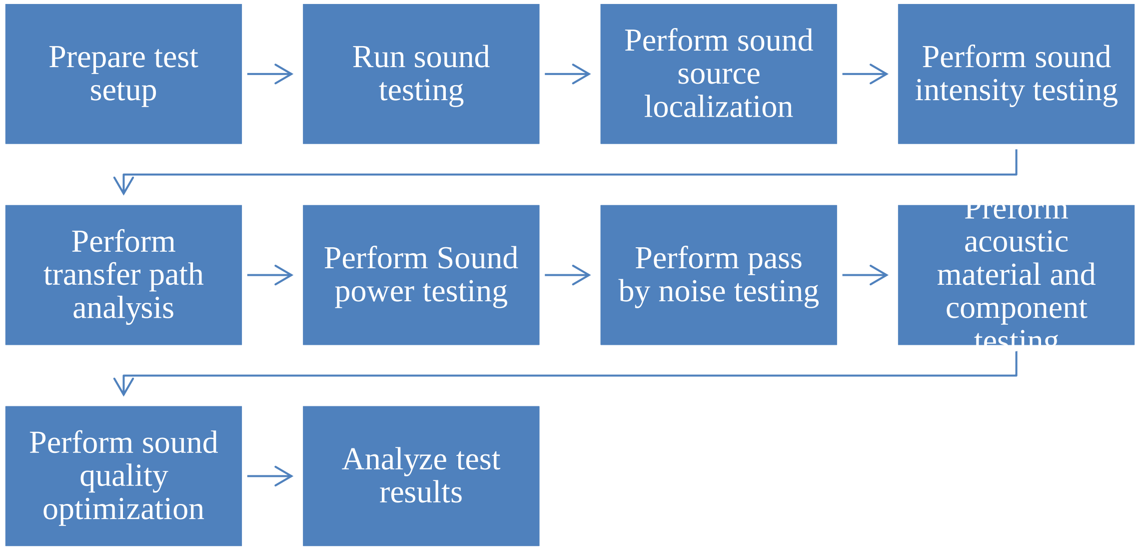

Figure 40 Typical Acoustic Testing & Optimization Process. Source: Author

Prepare Test Setup: The preparatory phase involves configuring test environments, instruments, and protocols tailored to specific acoustic testing requirements. Data science aids in this phase by leveraging historical data, simulation models, and predictive analytics to optimize test setups. By analyzing past test results, environmental factors, and product specifications, data science ensures that test setups are meticulously calibrated, facilitating accurate and reproducible acoustic assessments.

Run Sound Testing: Sound testing entails generating, recording, and analyzing acoustic signals emanating from products or environments under evaluation. Data science enhances this process by implementing automated testing frameworks, signal processing algorithms, and real-time analytics. By leveraging machine learning techniques, data science enables engineers to identify, isolate, and analyze acoustic signals with precision, ensuring comprehensive sound testing and validation.

Perform Sound Source Localization: Sound source localization focuses on identifying the spatial origin of acoustic emissions within complex systems or environments. Data science facilitates this process by leveraging array processing techniques, spatial algorithms, and machine learning models. By analyzing multi-channel acoustic data, data science enables engineers to pinpoint sound sources, assess localization accuracy, and optimize acoustic designs accordingly.

Perform Sound Intensity Testing: Sound intensity testing quantifies the distribution and propagation of acoustic energy within specified regions of interest. Data science augments this process by implementing advanced intensity mapping algorithms, spectral analysis techniques, and visualization tools. By leveraging computational models, data science enables engineers to measure sound intensity levels, identify hotspots, and optimize acoustic performance effectively.

Perform Transfer Path Analysis: Transfer Path Analysis (TPA) evaluates the transmission and propagation of sound energy through interconnected systems or components. Data science enhances TPA by implementing system identification techniques, frequency response analysis, and predictive modeling. By analyzing transfer functions, vibration data, and acoustic properties, data science enables engineers to assess energy transfer pathways, identify critical paths, and optimize system designs to minimize acoustic emissions.

Perform Sound Power Testing: Sound power testing quantifies the total acoustic energy radiated by products or systems under specified operating conditions. Data science facilitates this process by implementing sound power measurement techniques, spectral analysis, and statistical modeling. By leveraging measurement data, computational algorithms, and calibration protocols, data science enables engineers to quantify sound power levels accurately, assess compliance with regulatory standards, and optimize product designs.

Perform Pass-By Noise Testing: Pass-by noise testing evaluates the acoustic emissions of moving vehicles or equipment in real-world scenarios. Data science enhances this process by implementing sound propagation models, Doppler effect compensation techniques, and machine learning algorithms. By analyzing field data, environmental variables, and vehicle dynamics, data science enables engineers to assess pass-by noise levels, identify contributing factors, and optimize design parameters for enhanced acoustic performance.

Perform Acoustic Material and Component Testing: Acoustic material and component testing focus on evaluating the acoustic properties of materials, components, or subsystems within larger systems. Data science facilitates this process by implementing material characterization techniques, acoustic modeling, and simulation-driven analysis. By leveraging material data, acoustic metrics, and computational tools, data science enables engineers to assess material performance, optimize component designs, and enhance overall system acoustics.

Perform Sound Quality Optimization: Sound quality optimization aims to enhance the subjective perception and aesthetic appeal of acoustic emissions. Data science enhances this process by implementing psychoacoustic models, perceptual metrics, and optimization algorithms. By analyzing perceptual data, user feedback, and acoustic characteristics, data science enables engineers to refine sound quality parameters, optimize acoustic signatures, and align with user preferences and expectations.

Analyze Test Results: Analyzing test results constitutes the culmination of the Acoustic Testing & Optimization process, where engineers evaluate findings, derive insights, and formulate actionable recommendations. Data science enhances this phase by implementing advanced analytics, visualization tools, and machine learning techniques. By synthesizing test data, performance metrics, and simulation results, data science enables engineers to extract meaningful insights, identify optimization opportunities, and drive continuous improvement in acoustic performance.

In summary, the integration of data science into Acoustic Testing & Optimization redefines conventional methodologies, enabling engineers to achieve unparalleled levels of accuracy, efficiency, and innovation. By harnessing data-driven approaches across various sub-functions, data science empowers engineers to navigate complexities, optimize design strategies, and accelerate testing workflows, thereby reshaping the landscape of acoustic engineering and optimization (Bezzola, 2018; Guarnaccia et al., 2019; Haque et al., 2015; Heinrich et al., 2020; Rust et al., 2021).

4.1.3.6 Electrical Simulation

Electrical Simulation stands as a pivotal domain in modern engineering, focusing on the evaluation, analysis, and optimization of electrical systems and components. This section elaborates on the essential sub-functions as shown in *Figure 41* intrinsic to Electrical Simulation, elucidating the instrumental role of data science in amplifying its capabilities.

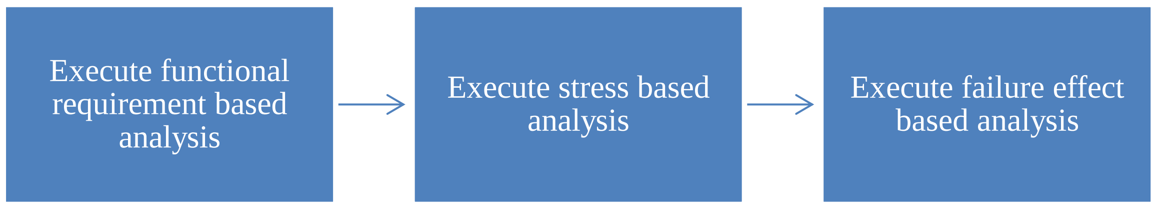

Figure 42 Typical Electrical Simulation Process. Source: Author

Execute Functional Requirement-Based Analysis: Functional requirement-based analysis entails evaluating electrical systems and components against specified performance criteria, functionalities, and operational parameters. Data science augments this analysis by leveraging algorithmic modeling, machine learning techniques, and optimization algorithms. By analyzing functional specifications, performance metrics, and simulation data, data science enables engineers to validate design compliance, optimize system configurations, and enhance overall performance reliability.

Execute Stress-Based Analysis: Stress-based analysis focuses on assessing the resilience, durability, and performance limits of electrical systems and components under varying operating conditions, environmental factors, and external influences. Data science facilitates stress-based analysis by implementing computational models, finite element analysis (FEA), and predictive analytics. By analyzing stress distributions, material properties, and environmental variables, data science enables engineers to identify potential failure points, mitigate risks, and optimize design parameters to ensure robustness and longevity.

Execute Failure Effect-Based Analysis: Failure effect-based analysis aims to evaluate the consequences, implications, and impact of potential failures within electrical systems and components. Data science enhances this analysis by implementing fault tree analysis (FTA), reliability modeling, and probabilistic risk assessment techniques. By analyzing failure modes, effects, and criticality, data science enables engineers to assess system vulnerabilities, prioritize mitigation strategies, and optimize design resilience against unforeseen contingencies.

In summary, the integration of data science into Electrical Simulation redefines conventional methodologies, enabling engineers to achieve unparalleled levels of accuracy, efficiency, and innovation. By harnessing data-driven approaches across various sub-functions, data science empowers engineers to navigate complexities, optimize design strategies, and accelerate simulation workflows, thereby reshaping the landscape of electrical engineering and analysis (Basole et al., 2019; Liu et al., 2009; Sajid et al., 2021; Zhang et al., 2009).

4.1.3.7 Simulation Data Management

Simulation Data Management (SDM) is a critical component in the realm of engineering and scientific research, ensuring that the vast amounts of data generated during simulation processes are organized, accessible, and actionable. This section delves into the multifaceted sub-functions as shown in *Figure 43* inherent to SDM and underscores the pivotal role of data science in enhancing its efficacy.

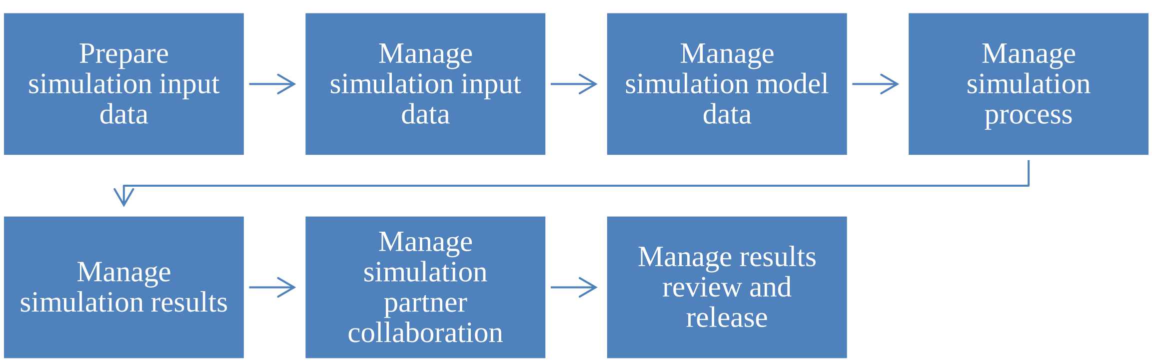

Figure 44 Typical Simulation Data Management. Source: Author

Prepare Simulation Input Data: Preparing simulation input data involves curating, preprocessing, and validating the data that serves as the foundation for various simulation processes. Data science plays a crucial role in this phase by automating data extraction, cleansing, and transformation tasks. By leveraging data analytics, machine learning algorithms, and pattern recognition techniques, data science ensures that input data are accurate, consistent, and optimized for subsequent simulation activities.

Manage Simulation Input Data: Managing simulation input data entails organizing, storing, and retrieving data sets, parameters, and configurations essential for simulation exercises. Data science facilitates this management by implementing data repositories, version control systems, and metadata catalogs. By leveraging data governance frameworks, access control mechanisms, and data lifecycle management strategies, data science ensures that simulation input data are secure, traceable, and readily accessible to authorized stakeholders.

Manage Simulation Model Data: Managing simulation model data focuses on curating, updating, and versioning computational models, algorithms, and simulation frameworks. Data science enhances this management by implementing model repositories, revision control systems, and validation workflows. By leveraging model metadata, dependency tracking, and provenance tracking techniques, data science ensures that simulation models are robust, reproducible, and compliant with industry standards and best practices.

Manage Simulation Process: Managing the simulation process involves orchestrating, monitoring, and optimizing computational workflows, resource allocations, and execution sequences. Data science facilitates this management by implementing workflow automation tools, scheduling algorithms, and performance monitoring dashboards. By leveraging predictive analytics, real-time monitoring, and optimization techniques, data science ensures that simulation processes are efficient, scalable, and aligned with organizational objectives.

Manage Simulation Results: Managing simulation results focuses on curating, analyzing, and disseminating outcomes, insights, and findings derived from simulation activities. Data science enhances this management by implementing result repositories, analytics platforms, and visualization tools. By leveraging data aggregation, analysis pipelines, and visualization techniques, data science ensures that simulation results are interpretable, actionable, and accessible to stakeholders across various disciplines.

Manage Simulation Partner Collaboration: Managing simulation partner collaboration entails fostering, coordinating, and facilitating collaborative efforts among internal teams, external partners, and stakeholders involved in simulation activities. Data science facilitates this collaboration by implementing collaborative platforms, communication frameworks, and shared repositories. By leveraging data integration, access control, and collaboration tools, data science ensures that partners can collaborate effectively, share knowledge, and collectively drive simulation initiatives.

Manage Results Review and Release: Managing results review and release focuses on evaluating, validating, and disseminating simulation results, insights, and recommendations to relevant stakeholders. Data science enhances this management by implementing review workflows, validation protocols, and release pipelines. By leveraging quality assurance, compliance checks, and approval mechanisms, data science ensures that simulation results are rigorously reviewed, validated, and released in accordance with organizational policies and regulatory requirements.

In summary, the integration of data science into Simulation Data Management redefines conventional methodologies, enabling stakeholders to achieve unparalleled levels of efficiency, accuracy, and collaboration. By harnessing data-driven approaches across various sub-functions, data science empowers stakeholders to navigate complexities, optimize workflows, and accelerate simulation initiatives, thereby reshaping the landscape of engineering simulation and data management (Abdulla et al., 2004; Dayıbaş et al., 2019; Robertson & Perera, 2002; Sajid et al., 2021).

4.1.3.8 Mitigation Strategies for Challenges in Adoption of Data Science

The table delineates the integration of Data Science use cases within various processes of the Design Simulation and Exploration function. For each process, specific Data Science based applications are identified, ranging from optimization algorithms and predictive analytics to real-time monitoring and feedback mechanisms. These Data Science applications align with distinct business agility goals, such as improving behavioral and situational awareness, enabling inclusive and augmented decision-making, and creating dynamic processes and resources for fast execution.

Table 3 Data Science Use Cases for the various process in Design Simulation and Exploration function. Source: Author

Process	**Data Science Use Cases**	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
1D Multiphysics System Simulation	Optimization algorithms for system parameters	Improve Behavioral Awareness	Lack of skilled workforce	Project delays due to unskilled labor	Training programs, hiring skilled experts
1D Multiphysics System Simulation	Predictive analytics for performance metrics	Enable augmented decision making	Data quality and availability	Inaccurate simulation outcomes	Data cleansing, validation, and integration
1D Multiphysics System Simulation	Real-time monitoring and feedback mechanisms	Create dynamic processes for fast execution	Integration with existing systems	System inefficiencies and inconsistencies	Integration protocols, system compatibility checks
3D CAE Simulation	Automated meshing and	Improve Situational Awareness	Privacy and security concerns	Data breaches, unauthorized access	Encryption, access controls,

Table 3 Data Science Use Cases for the various process in Design Simulation and Exploration function. Source: Author					
Process	**Data Science Use Cases**	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
	geometric analysis				data anonymization
3D CAE Simulation	Structural optimization using machine learning algorithms	Enable Inclusive decision making	Scalability	Performance bottlenecks, system crashes	Cloud-based solutions, distributed computing
CCM & CFD Simulation and Design Impact	Turbulence modelling and optimization techniques	Create dynamic resources for fast execution	Alignment with business objectives	Misaligned strategies, wasted resources	Stakeholder alignment, strategy refinement
CCM & CFD Simulation and Design Impact	Predictive analytics for design impact prediction	Improve Behavioral Awareness	Lack of standardization	Inconsistencies in simulation outputs	Standardization protocols, best practices adoption
Virtual Product Visualization & Validation	AR, VR, and MR technologies for immersive visualization	Improve Situational Awareness	Lack of skilled workforce	Project delays due to unskilled labor	Training programs, hiring skilled experts
Virtual Product Visualization & Validation	3D modelling and simulation-driven design	Enable augmented decision making	Integration with existing systems	System inefficiencies and inconsistencies	Integration protocols, system compatibility checks

Table 3 Data Science Use Cases for the various process in Design Simulation and Exploration function. Source: Author

Process	**Data Science Use Cases**	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Acoustic Testing & Optimization	Signal processing algorithms for noise mitigation	Improve Behavioral Awareness	Data quality and availability	Inaccurate simulation outcomes	Data cleansing, validation, and integration
Acoustic Testing & Optimization	Noise mapping and acoustic modelling	Enable Inclusive decision making	Privacy and security concerns	Data breaches, unauthorized access	Encryption, access controls, data anonymization
Electrical Simulation	Circuit analysis tools and electromagnetic modelling	Create dynamic processes for fast execution	Lack of standardization	Inconsistencies in simulation outputs	Standardization protocols, best practices adoption
Electrical Simulation	System optimization using machine learning algorithms	Enable augmented decision making	Integration with existing systems	System inefficiencies and inconsistencies	Integration protocols, system compatibility checks
Simulation Data Management	Data repositories, version control systems	Improve Situational Awareness	Lack of skilled workforce	Project delays due to unskilled labor	Training programs, hiring skilled experts

Table 3 Data Science Use Cases for the various process in Design Simulation and Exploration function. Source: Author					
Process	**Data Science Use Cases**	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Simulation Data Management	Data governance, access control mechanisms	Enable Inclusive decision making	Privacy and security concerns	Data breaches, unauthorized access	Encryption, access controls, data anonymization

However, the adoption of Data Science within these processes is accompanied by inherent challenges that organizations must navigate. These challenges encompass a lack of skilled workforce, data quality and availability issues, integration complexities with existing systems, privacy and security concerns, scalability limitations, misalignment with business objectives, and a lack of standardization. Each challenge presents associated risks, including project delays, inaccurate simulation outcomes, system inefficiencies, data breaches, and inconsistencies.

To mitigate these challenges and associated risks, organizations must implement tailored mitigation strategies as detailed in *Table 3*. These strategies encompass a multifaceted approach, incorporating training programs, data cleansing and validation, integration protocols, encryption, access controls, cloud-based solutions, stakeholder alignment, and standardization protocols. By proactively addressing these challenges and risks, organizations can harness the transformative potential of Data Science, optimize operational efficiency, drive innovation, and achieve strategic objectives in the competitive landscape of design simulation and exploration.

4.1.4 Mitigation Strategies for Challenges in Adoption of Data Science in Mechanical Design function

In the contemporary landscape of engineering and design, the infusion of data science into traditional mechanical functions has become increasingly vital. This section explores the application of data science methodologies within three key domains of mechanical design: Mechanical Design Management, Fastened Structures Mechanical Design, and Generative Mechanical Design. This section discusses, how the integration of data science in mechanical design functions revolutionizes traditional processes, fostering efficiency, innovation, and reliability. By leveraging data-driven insights, mechanical design teams can navigate the complexities of their domains with enhanced precision, ultimately contributing to the advancement of engineering practices (Hamrol et al., 2023; Hinojosa-Palafox et al., 2019; Setiyo et al., 2021; Shafiq et al., 2019; Silva et al., 2020; Yin & Qin, 2019).

4.1.4.1 Mechanical Design Management

The integration of data science into Mechanical Design Management functions marks a transformative era in engineering practices, revolutionizing the conventional processes of product development. In the intricate landscape of mechanical design, where precision, efficiency, and informed decision-making are paramount, data science emerges as a catalyst for innovation. This section explores the multifaceted applications of data science across key business processes as shown in *Figure 45* within Mechanical Design Management. From performing design studies to managing design libraries, data science introduces a data-driven paradigm that not only expedites traditional processes but also enhances the overall quality and reliability of mechanical designs. By delving into the nuances of each business process, this work uncovers how data science empowers engineers to make more informed decisions, optimize design outcomes, and streamline the entire mechanical design lifecycle.

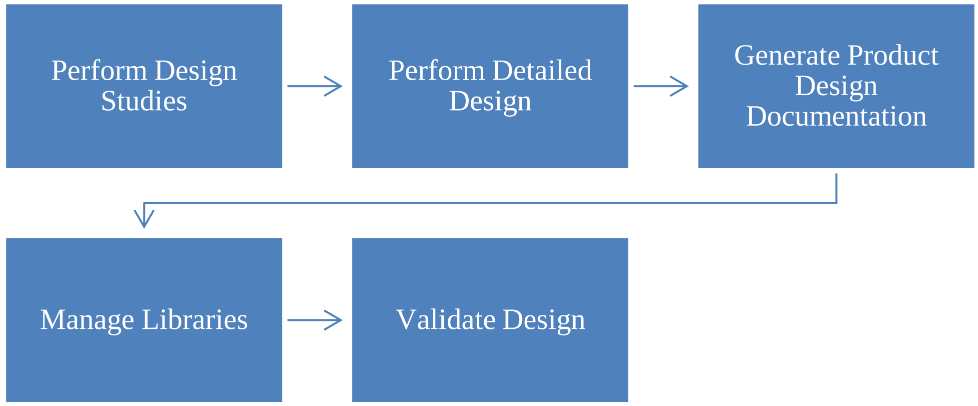

Figure 46 Mechanical Design Management. Source: Author

Perform Design Studies: In the realm of design studies, data science plays a pivotal role in enhancing the decision-making process. Through the analysis of historical design data, including performance metrics and project outcomes, engineers can identify patterns and trends. This enables more informed design decisions, as well as the ability to anticipate potential challenges, leading to optimized design solutions.

Perform Detailed Design: Data science facilitates a comprehensive approach to detailed design by leveraging predictive modeling. Engineers can utilize advanced algorithms to simulate and analyze various design scenarios, predicting the performance of different components or systems. This not only accelerates the design process but also ensures that the final detailed design aligns with performance expectations.

Generate Product Design Documentation: Efficient documentation is crucial for effective communication within a design management function. Data science aids in automating the generation of product design documentation by extracting relevant information from design databases and project repositories. This not only reduces manual effort but also minimizes the likelihood of errors in documentation, contributing to improved overall project efficiency.

Manage Libraries: Data science supports efficient library management by automating the organization and categorization of design components. Through machine learning algorithms, the system can learn from past usage patterns, suggesting relevant components for new projects. This not only streamlines the design process but also ensures consistency in component selection across different projects.

Validate Design: Validation of design is a critical aspect of ensuring product performance and reliability. Data science assists in the validation process by analyzing real-time sensor data from prototypes or simulations. Engineers can identify discrepancies between expected and actual performance, enabling timely adjustments to the design. This proactive validation approach contributes to the production of more robust and reliable designs.

In conclusion, the integration of data science in Mechanical Design Management functions revolutionizes the way design processes are executed. From informed decision-making in design studies to automated documentation generation and enhanced validation processes, data science brings efficiency and precision to every stage of the mechanical design lifecycle (Du & Zhu, 2018; Giess & Culley, 2003; Li, 2004; Steingrimsson et al., 2018; Volpentesta et al., 2004; Zadeh & Shahbazy, 2020).

4.1.4.2 Fastened Structures Mechanical Design

Within the domain of Product Design and Development, the integration of data science into Fastened Structures Mechanical Design activities offers opportunities for enhanced efficiency and precision. This section explores how data science can be applied to activities as shown in *Figure 47* involving the definition of fastener design rules, maintenance of standard parts libraries, preliminary joint sizing, detailed joint design definition, joint design validation, fastener product documentation development, and manufacturing information generation.

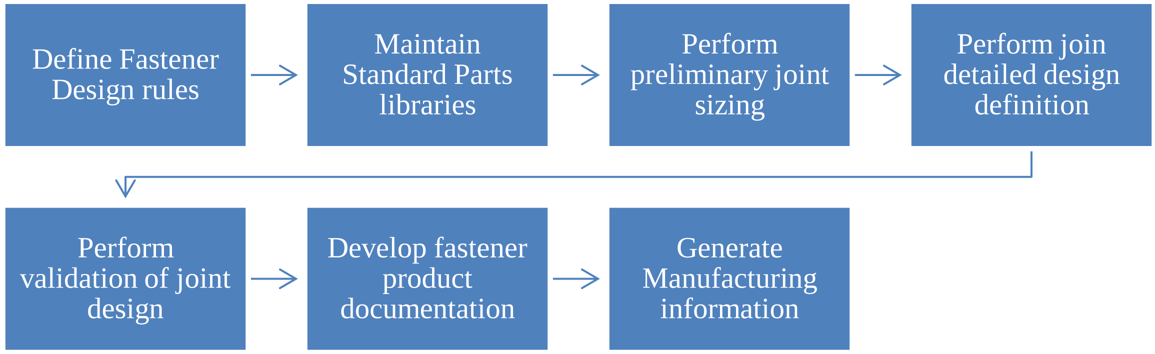

Figure 48 Typical Fastened Structures Mechanical Design Workflow. Source: Author

Data Science in Fastened Structures Mechanical Design:

The definition of fastener design rules benefits from data science through rule-based systems that analyze historical design data. Machine learning algorithms can identify patterns and correlations, assisting in the formulation of design rules that align with optimal fastener performance.

Maintaining standard parts libraries is streamlined with data-driven approaches. Machine learning models can analyze usage patterns, material characteristics, and historical library data to suggest updates, additions, or retirements of standard parts, ensuring the library remains relevant and efficient.

Preliminary joint sizing is optimized through data science by employing algorithms that consider diverse factors, such as material properties, load conditions, and historical joint performance data. Predictive models can recommend preliminary joint sizes, reducing the need for iterative adjustments in the later stages of design.

Detailed joint design definition benefits from automated processes driven by data science. Natural Language Processing (NLP) algorithms can assist in interpreting design requirements, ensuring detailed design specifications align with predefined rules and standards.

Validation of joint design is enhanced by data science through simulation and modeling. Machine learning models can predict potential issues or failure points, enabling proactive adjustments to the joint design before physical prototyping, thereby saving time and resources.

Fastener product documentation development is facilitated by data-driven systems. Automated documentation generation tools, leveraging historical data and design rules, ensure the accuracy and completeness of product documentation, reducing the likelihood of errors.

Generating manufacturing information is streamlined through data science by automating the extraction of relevant details from the design and documentation. This ensures that manufacturing information aligns with the designed parameters, reducing discrepancies between design intent and manufacturing execution.

In summary, the integration of data science into Fastened Structures Mechanical Design within the broader context of Product Design and Development brings forth improvements in designing rules, maintaining libraries, sizing joints, defining joint details, validating designs, and generating documentation and manufacturing information. This data-centric approach contributes to the precision, efficiency, and overall optimization of the fastened structures design process (Li, 2004; Nguyen, 2021; Sandhya, 2020; Zadeh & Shahbazy, 2020).

4.1.4.3 Generative Mechanical Design

Within the realm of Product Design and Development, the incorporation of data science into Generative Mechanical Design processes as shown in *Figure 49* holds promise for optimizing various design activities. This section explores how data science can be applied to define design constraints and requirements, define materials, develop decision algorithms, configure generation environments, execute design generation, compare design alternatives, develop prototypes, manage design exploration, oversee the design concept and selection process, design for manufacturing, and review and release designs.

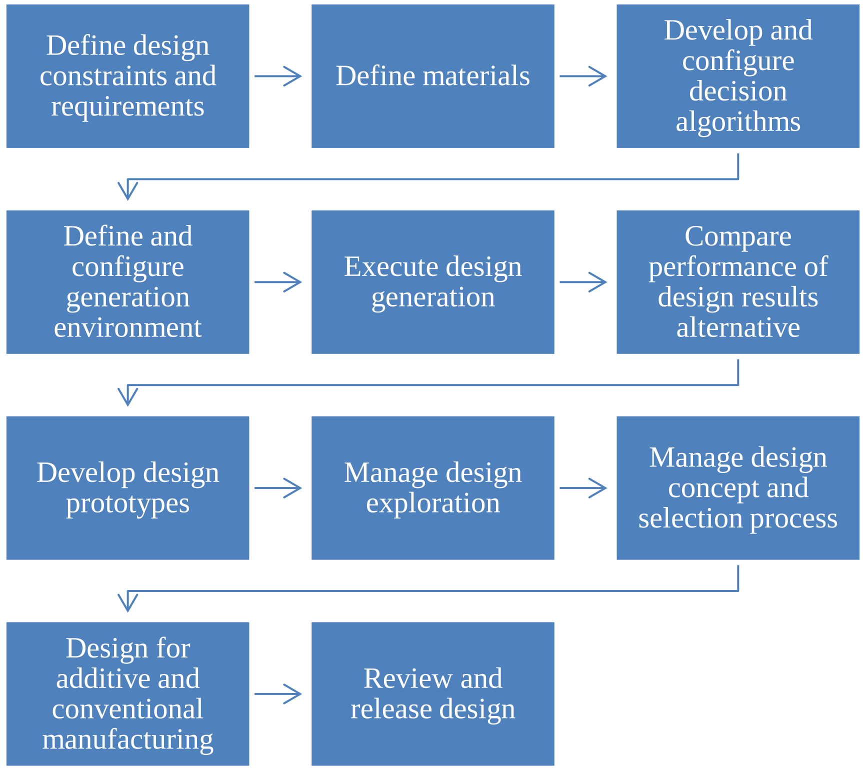

Figure 50 Typical Generative Mechanical Design Process Flow. Source: Author

Data science contributes to defining design constraints and requirements by analyzing historical design data and market trends. Machine learning models can extract valuable insights, enabling more informed decisions about design specifications and constraints.

Defining materials benefits from data science through material analysis algorithms. These algorithms assess material properties, historical performance, and market availability, assisting in the selection of optimal materials for a given design.

Developing and configuring decision algorithms is facilitated by data science, employing machine learning models to automate decision-making processes. These algorithms can consider various factors, such as cost, performance, and sustainability, to generate data-driven decisions.

Defining and configuring generation environments is optimized through data-driven approaches. Machine learning models can analyze environmental factors, project requirements, and historical design success, aiding in the configuration of generation environments that enhance design outcomes.

Executing design generation is streamlined by data science, incorporating optimization algorithms and generative design techniques. These techniques consider a multitude of parameters to generate design alternatives that meet specified criteria efficiently.

Comparing the performance of design alternatives is enhanced by data science-driven analytics. Machine learning models can evaluate design alternatives based on predefined metrics, providing objective insights into their strengths and weaknesses.

Developing design prototypes benefits from data science through virtual prototyping. Simulation models, guided by machine learning algorithms, can predict the performance of prototypes, reducing the need for physical iterations and accelerating the design iteration cycle.

Managing design exploration is facilitated by data science tools that analyze and visualize design exploration paths. These tools can provide designers with insights into the impact of design decisions, supporting a more informed exploration process.

Overseeing the design concept and selection process involves data-driven decision support systems. Machine learning models can assist in evaluating design concepts against predefined criteria, aiding designers in selecting the most viable concepts for further development.

Designing for both additive and conventional manufacturing processes is optimized by data science. Simulation models can assess the manufacturability of designs, considering manufacturing constraints and requirements for both additive and conventional methods.

Reviewing and releasing designs is facilitated by data-driven quality assurance tools. Machine learning algorithms can analyze design data to identify potential issues, ensuring that released designs meet established standards and requirements.

In summary, the integration of data science into Generative Mechanical Design processes within the broader context of Product Design and Development results in more informed decision-making, streamlined design iterations, and enhanced design outcomes. From defining constraints and materials to executing design generation and managing the selection process, data science offers a comprehensive approach to optimizing the entire design lifecycle (Chaszar et al., 2016; Du & Zhu, 2018; Kun et al., 2018; Nagaraj & Werth, 2020; Zadeh & Shahbazy, 2020).

4.1.4.4 Mitigation Strategies for Challenges in Adoption of Data Science in Mechanical Design function

Below shown *Table **4*** outlines the strategic integration of data science use cases in various mechanical design processes, emphasizing their impact on business agility goals. The use cases span from predicting design performance to optimizing manufacturing information generation. Each Data Science use case is mapped to specific business agility goals, such as improving situational awareness, enabling inclusive decision-making, and creating dynamic processes and resources for fast execution. However, organizations may encounter challenges in implementing these use cases. These challenges, including a lack of skilled workforce, data quality issues, integration difficulties, privacy concerns, scalability challenges, misalignment with business objectives, and lack of standardization, pose potential risks. The associated risks include compromised design integrity, inaccurate predictions, workflow disruptions, and potential security breaches. To mitigate these challenges and risks, organizations can adopt targeted strategies. These strategies include investing in workforce training, implementing data quality checks and governance practices, conducting thorough system compatibility assessments, addressing privacy and security concerns through encryption and access controls, investing in scalable infrastructure, and enforcing standardized procedures.

Table 4 Data Science Use Cases for the various process in Mechanical Design function. Source: Author

Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
Mechanical Design Management	Perform Design Studies: Utilize machine learning to predict design performance based on historical data.	Lack of skilled workforce: Limited expertise in machine learning techniques.	Ineffective use of AI models, potential errors in predictions.	Provide training programs, collaborate with external experts, and invest in skill development.
Mechanical Design Management	Perform Detailed Design: Implement machine learning for automated aspects of detailed design.	Data quality and availability: Incomplete or unreliable design data.	Inaccurate automated designs, compromised design integrity.	Implement data quality checks, invest in data cleansing tools, and establish data governance practices.
Mechanical Design Management	Generate Product Design Documentation: Use NLP algorithms for data-driven document generation.	Integration with existing systems: Difficulty integrating NLP algorithms with current documentation systems.	Workflow disruptions, inconsistent documentation.	Conduct thorough system compatibility assessments, work with IT teams to ensure seamless integration.

Table 4 Data Science Use Cases for the various process in Mechanical Design function. Source: Author				
Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
Mechanical Design Management	Manage Libraries: Optimize library management using data analytics.	Privacy and security concerns: Protecting sensitive design data.	Unauthorized access, data breaches.	Implement robust encryption, access controls, and regular security audits.
Mechanical Design Management	Validate Design: Apply machine learning for predicting potential design flaws.	Scalability: Challenges in scaling machine learning models for larger datasets.	Performance degradation, increased processing time.	Invest in scalable infrastructure, consider cloud-based solutions, and optimize algorithms for efficiency.
Fastened Structures Mechanical Design	Define Fastener Design Rules: Utilize data-driven analysis for optimal rules.	Alignment with business objectives: Design rules may not align with current business goals.	Inefficient design processes, mismatched design outcomes.	Regularly review and update design rules based on evolving business objectives.
Fastened Structures Mechanical Design	Maintain Standard Parts Libraries: Dynamically update libraries based on data analytics.	Lack of standardization: Inconsistencies in standard part libraries.	Inaccurate design outcomes, compatibility issues.	Implement and enforce standardized procedures for library updates and maintenance.

Table 4 Data Science Use Cases for the various process in Mechanical Design function. Source: Author

Process	Data Science Use Cases	Challenges	Risk	Mitigation Strategies
Fastened Structures Mechanical Design	Perform Preliminary Joint Sizing: Use data science for predicting sizing requirements.	Lack of skilled workforce: Insufficient knowledge in data science for joint sizing.	Inaccurate sizing predictions, potential joint failures.	Provide specialized training, collaborate with external experts, and invest in joint sizing expertise.
Fastened Structures Mechanical Design	Perform Validation of Joint Design: Apply machine learning for analyzing past validation data.	Data quality and availability: Incomplete or unreliable validation data.	Inaccurate validation predictions, compromised joint integrity.	Implement data quality checks, invest in data cleansing tools, and establish data governance practices.
Fastened Structures Mechanical Design	Generate Manufacturing Information: Optimize data-driven manufacturing information generation.	Integration with existing systems: Difficulty integrating data-driven processes with current manufacturing systems.	Workflow disruptions, inconsistent manufacturing information.	Conduct thorough system compatibility assessments, work with IT teams to ensure seamless integration.

Table 4 Data Science Use Cases for the various process in Mechanical Design function. Source: Author				
Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
Generative Mechanical Design	Define Design Constraints and Requirements: Assist in analyzing diverse requirements.	Privacy and security concerns: Protecting sensitive design constraint data.	Unauthorized access, data breaches.	Implement robust encryption, access controls, and regular security audits.
Generative Mechanical Design	Develop and Configure Decision Algorithms: Train algorithms for automated decision-making.	Scalability: Challenges in scaling decision-making algorithms.	Performance degradation, increased processing time.	Invest in scalable infrastructure, consider cloud-based solutions, and optimize algorithms for efficiency.
Generative Mechanical Design	Design for Additive and Conventional Manufacturing: Guide generative design for both manufacturing methods.	Lack of standardization: Inconsistencies in design outputs for different manufacturing methods.	Inefficient design processes, production delays.	Implement and enforce standardized procedures for design outputs.

Table 4 Data Science Use Cases for the various process in Mechanical Design function. Source: Author				
Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
Generative Mechanical Design	Review and Release Design: Streamline the review process using data analytics.	Alignment with business objectives: Designs may not align with current business goals.	Inefficient review processes, potential design misalignments.	Regularly review and update design criteria based on evolving business objectives.

As summarized in *Table 4,* the systematic integration of data science use cases into mechanical design processes not only enhances efficiency and accuracy but also aligns with key business agility goals. Addressing challenges proactively and implementing effective mitigation strategies will ensure the successful adoption of data science in the mechanical design domain, fostering innovation and competitiveness.

4.1.5 Electrical & Electronic Design

Within the realm of Product Design and Development, particularly focusing on Electrical & Electronic Design, the incorporation of data science holds significant promise in optimizing various design activities. This section explores how data science can be effectively applied to activities such as EE (Electrical and Electronic) Architecture & Systems Design, Electrical System Design - Generative, Electrical Design Management, Electrical Harness Design, PCB Design Management, EE Component & Library Management, and Integrated Circuit Design. The following sections will discuss in detail about each process that is listed below and discuss the different data science uses cases that can be orchestrated. The integration of data science into Electrical & Electronic Design activities within the broader context of Product Design and Development leads to improvements in architectural design prediction, generative system design, project management, harness and PCB design efficiency, library management, and integrated circuit optimization. This data-centric approach fosters innovation, efficiency, and reliability in the electrical and electronic design processes (Alajbeg & Sokele, 2019; Aly, 2010; Lehtla et al., 2011; Liu & Chen, 2017; Tüchsen et al., 2018).

4.1.5.1 EE Architecture & Systems Design

In the realm of Product Design and Development, particularly in the Electrical & Electronic Design function, the integration of data science into Electrical & Electronic (EE) Architecture and Systems Design activities brings about significant advancements. This section explores the application of data science in activities as shown in *Figure 51* such as associating and allocating functions to platform design, creating EE platform architectures, developing functional designs, capturing requirements and constraints, simulating, calibrating, conducting verification and validation, and evaluating and optimizing EE architectures.

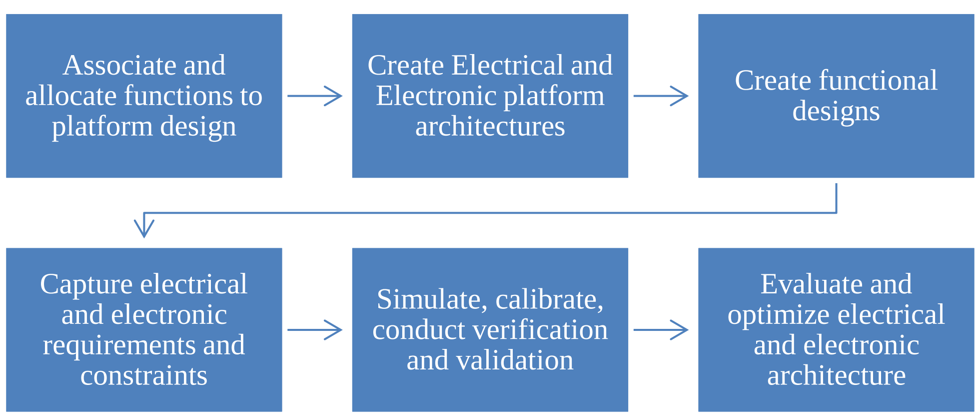

Figure 52 Electrical and Electronics Architecture & Systems Design function. Source: Author

Data Science in EE Architecture & Systems Design:

Associating and Allocating Functions to Platform Design: Data science contributes to associating and allocating functions by analyzing historical data and functional relationships. Machine learning models can identify patterns in past design decisions, optimizing the association and allocation of functions to platforms based on proven methodologies and successful implementations (Dietermann et al., 2013).

Creating Electrical and Electronic Platform Architectures: Data-driven design optimization is achieved through machine learning algorithms that analyze various architectural possibilities. By considering historical architectures, performance metrics, and design constraints, data science assists in creating EE platform architectures that align with project goals and specifications (Yao & Rabhi, 2015).

Creating Functional Designs: Functional design benefits from data science by incorporating optimization algorithms. Machine learning models can analyze functional requirements, historical design choices, and performance data to recommend optimal functional designs that balance efficiency and effectiveness (Bayrak & Cebeci, 2012).

Capturing Electrical and Electronic Requirements and Constraints: Data science facilitates the capture of requirements and constraints through automated analysis tools. Natural Language Processing (NLP) algorithms can process textual documents to extract essential information, ensuring that captured requirements are comprehensive and aligned with project objectives.

Simulating, Calibrating, Conducting Verification and Validation: Simulation and verification processes are enhanced by data science through predictive modeling. Machine learning models can simulate and predict system behavior, calibrate parameters, and automate verification and validation procedures. This ensures a more efficient and accurate validation process (Hillenbrand et al., 2012).

Evaluating and Optimizing Electrical and Electronic Architecture: Data science-driven optimization models contribute to the evaluation and optimization of EE architectures. By analyzing historical performance data, design iterations, and constraints, machine learning algorithms recommend adjustments to optimize the architecture's efficiency, reliability, and compliance with specified criteria.

In summary, the integration of data science into EE Architecture & Systems Design activities within Electrical & Electronic Design offers a data-centric approach to design optimization, simulation, verification, and architecture evaluation. Leveraging machine learning models and predictive analytics, organizations can achieve more efficient and effective design processes, ultimately contributing to the advancement of Product Design and Development in the Electrical & Electronic domain (Bayrak & Cebeci, 2012; Dietermann et al., 2013; Ge et al., 2013; Hillenbrand et al., 2012; Yao & Rabhi, 2015).

4.1.5.2 Electrical System Design – Generative

In the realm of Product Design and Development, specifically within the Electrical & Electronic Design function, the integration of data science into Electrical System Design – Generative processes as shown in *Figure 53*, offers opportunities for innovation and optimization. This section explores how data science can be applied to activities such as defining design rules, topology, bundle diameters, wirelengths, logical design, design data exchange, wiring synthesis, 3D routing, schematic generation, physical system architecture optimization, design validation, and wiring design release.

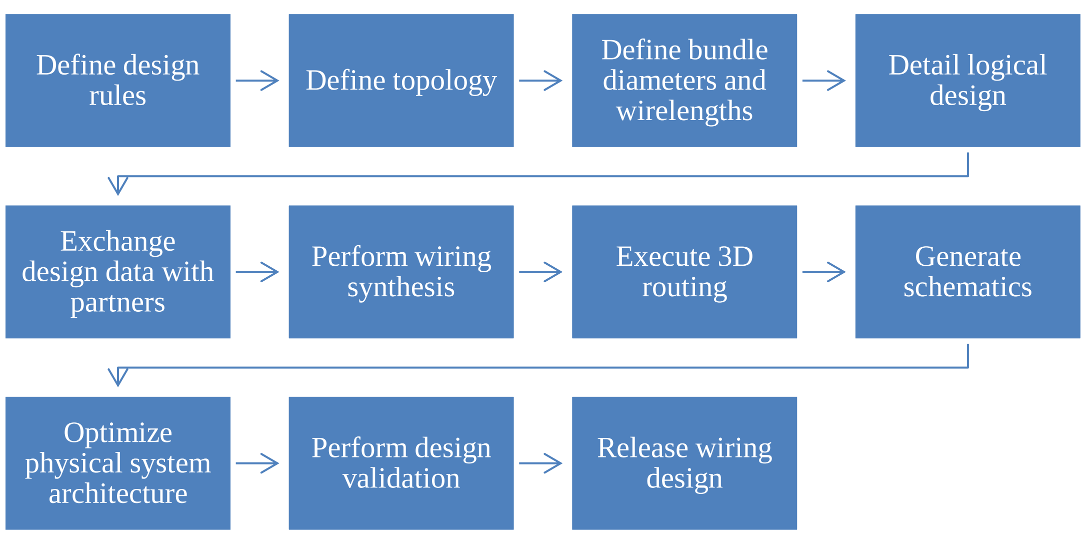

Figure 54 Electrical System Generative Design Process Flow. Source: Author

Define Design Rules and Topology: Data science contributes to defining design rules and topology by analyzing historical design data and industry standards. Machine learning algorithms can identify patterns in successful designs, enabling the formulation of rules and topologies that align with proven practices and enhance overall design efficiency (Bodenbenner et al., 2013).

Define Bundle Diameters and Wirelengths: Machine learning models can analyze historical data on bundle diameters and wirelengths to provide insights into optimal configurations. This data-driven approach ensures that defined diameters and lengths are based on real-world performance metrics, promoting efficiency, and reducing potential design errors.

Detail Logical Design and Exchange Design Data: Data science aids in detailing logical design by automating processes through Natural Language Processing (NLP) and semantic analysis. Furthermore, data science facilitates the exchange of design data with partners by developing interoperable data formats and protocols, ensuring seamless collaboration (Chernova, 2018).

Perform Wiring Synthesis and Execute 3D Routing: Wiring synthesis is optimized through data-driven algorithms that consider factors like signal integrity and manufacturability. Additionally, data science enhances 3D routing by utilizing machine learning models to analyze spatial constraints and optimize routing paths, ensuring efficient and reliable electrical systems.

Generate Schematics and Optimize Physical System Architecture: Generative AI, such as Language Models (LLM), aids in automatically generating schematics based on specified criteria. Furthermore, data science supports the optimization of physical system architecture by analyzing performance data and suggesting improvements in component placement and connectivity (Scheer & Dolezilek, 2007).

Perform Design Validation and Release Wiring Design: Data science enables automated design validation by developing models that simulate and analyze system behavior. This ensures that the design meets performance requirements before physical implementation. Subsequently, the release of wiring design is streamlined through automated validation processes, reducing the likelihood of errors and rework.

In summary, the integration of data science into Electrical System Design – Generative processes within Electrical & Electronic Design functions enhances various aspects of the design lifecycle. From defining rules and topologies to automating wiring synthesis, 3D routing, and schematic generation, data science promotes efficiency, accuracy, and collaboration. This data-centric approach ensures that electrical designs are not only innovative but also aligned with industry best practices and standards (Bodenbenner et al., 2013; Chernova, 2018; Scheer & Dolezilek, 2007).

4.1.5.3 Electrical Design Management

Within the organizational context of Product Design and Development, specifically in the Electrical & Electronic Design function, the integration of data science holds promises for optimizing Electrical Design Management process flow as shown in *Figure 55*. This section delves into how data science can be applied to the breakdown of system constraints to domain level, defining cabinet layouts, reviewing electrical designs, defining electrical schematics, routing cables, and validating and releasing electrical designs.

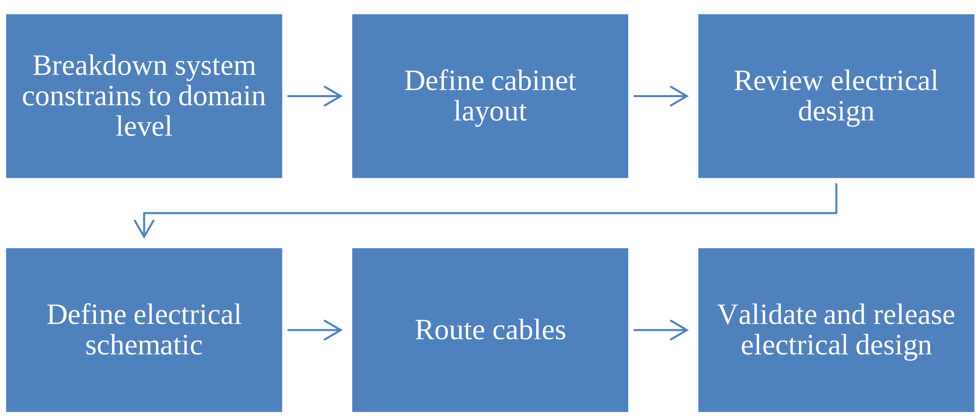

Figure 56 Electrical Design Management Process Flow. Source: Author

Breakdown System Constraints to Domain Level: Data science methodologies, such as machine learning algorithms, can assist in breaking down system constraints to domain level by analyzing historical design data. These algorithms can identify patterns and relationships within complex system constraints, providing insights into domain-specific constraints that may impact electrical design (Bertozzi et al., 2023).

Define Cabinet Layout: Optimizing cabinet layouts can be achieved through data-driven approaches. Machine learning models can analyze spatial relationships, electrical component requirements, and historical layout data to propose efficient and effective cabinet designs (Bodenbenner et al., 2013).

Review Electrical Design: Automated review processes, driven by data science, can enhance the accuracy and efficiency of electrical design reviews. Machine learning algorithms can evaluate design parameters, adherence to standards, and historical review data to identify potential issues or areas for improvement (Chernova, 2018).

Define Electrical Schematic: Data science contributes to defining electrical schematics by automating the analysis of complex electrical configurations. Natural Language Processing (NLP) algorithms can interpret textual descriptions and historical schematic data to assist in the generation of detailed and accurate electrical schematics (Fockema, 2014).

Route Cables: Efficient cable routing can benefit from data-driven optimization. Machine learning algorithms can consider factors such as component locations, cable lengths, and historical routing data to propose optimal cable routes that minimize interference and maximize efficiency (Guo et al., 2018).

Validate and Release Electrical Design: Data science facilitates the validation and release of electrical designs through automated validation processes. Predictive analytics models can assess the quality, compliance, and historical performance of electrical designs, ensuring that only validated designs are released for further development or production.

In summary, the integration of data science into Electrical Design Management activities offers a multifaceted approach to optimizing processes within the Product Design and Development organization. From breaking down system constraints to proposing efficient cabinet layouts, automating design reviews, and optimizing cable routing, data science enhances the accuracy, efficiency, and overall effectiveness of electrical design processes (Bertozzi et al., 2023; Bodenbenner et al., 2013; Chernova, 2018; Fockema, 2014; Guo et al., 2018).

4.1.5.4 Electrical Harness Design

Electrical Harness Design, a critical facet of the broader Electrical & Electronic Design function within the Product Design and Development organization, plays a pivotal role in modern engineering endeavors. This section explores the integration of data science into various Electrical Harness Design activities as shown in *Figure 57*, encompassing the definition of harness models, automated parts selection, 3D routing, design validation, harness design exchange with partners, and the release of harness designs.

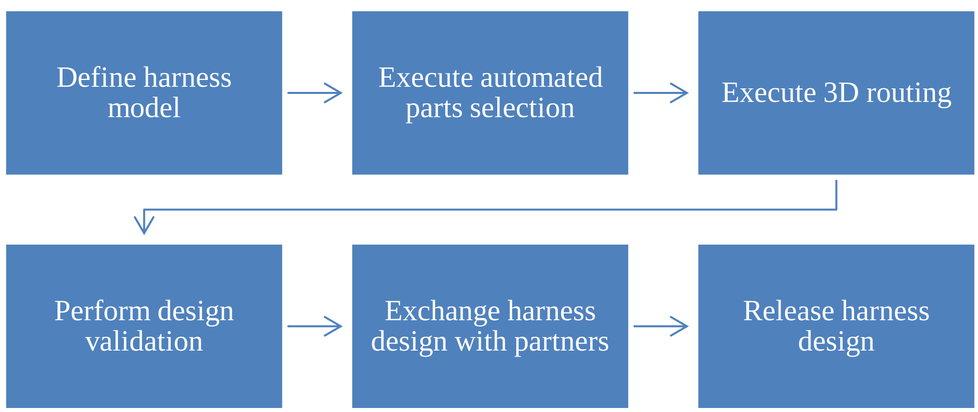

Figure 58 Electrical Harness Design Process Flow. Source: Author

Define Harness Model: Data science augments the definition of harness models by leveraging historical design data and contextual information. Machine learning models, as indicated by studies (Bodenbenner et al., 2013), can predict optimal harness configurations based on past designs, improving the efficiency and accuracy of model definition in Electrical Harness Design.

Execute Automated Parts Selection: Automated parts selection is enhanced by data science through the utilization of algorithms that consider historical part usage, performance, and compatibility data. These algorithms, as discussed in studies (Fedorov & Ferenetz, 2017), ensure that the selection process is optimized for efficiency, cost-effectiveness, and compliance with design requirements.

Execute 3D Routing: Data science-driven 3D routing involves the application of machine learning models to analyze spatial constraints, historical routing data, and design parameters. This facilitates the generation of optimized 3D routes, as supported by research findings (Chernova, 2018), contributing to efficient and error-free harness designs.

Perform Design Validation: Design validation is expedited through data science by employing predictive analytics models. These models evaluate design parameters against historical validation data and predefined standards, as highlighted by studies (Tüchsen et al., 2018), ensuring that the harness design meets specified criteria and minimizing the need for manual validation efforts.

Exchange Harness Design with Partners: The exchange of harness designs with partners benefits from data science-driven collaboration platforms. These platforms, integrating NLP algorithms (Riba et al., 2022), facilitate seamless communication, ensuring that design information is accurately interpreted and exchanged among collaborators, thereby enhancing overall collaboration efficiency.

Release Harness Design: The release of harness designs is streamlined through data science-driven systems. Predictive analytics models assess the readiness of designs for release by considering factors such as compliance, quality, and historical design success, aligning with research insights (Madhavi & Satyanarayana, 2022) to enhance the reliability of the release process.

In summary, the integration of data science into Electrical Harness Design activities within the domain of Electrical & Electronic Design significantly contributes to the efficiency, accuracy, and collaboration aspects of the design process. Leveraging machine learning models, predictive analytics, and NLP algorithms ensures a data-centric approach that aligns with industry research findings, ultimately advancing the effectiveness of Electrical Harness Design in the broader context of Product Design and Development (Bodenbenner et al., 2013; Chernova, 2018; Fedorov & Ferenetz, 2017; Madhavi & Satyanarayana, 2022; Riba et al., 2022; Tüchsen et al., 2018).

4.1.5.5 PCB Design Management

Within the domain of Product Design and Development, specifically focusing on Electrical & Electronic Design, the application of data science in PCB (Printed Circuit Board) Design Management introduces a data-driven approach to various critical activities as shown in *Figure 59*. This section explores how data science can be effectively employed in tasks related to defining Electrical Computer-Aided Design (ECAD) of printed circuit boards, signal allocation, schematic design development, electronic library management, layout design development, defining ECAD dependencies, electronic simulation execution, manufacturability validation, manufacturing data creation, and design release validation.

Data Science in PCB Design Management:
Data science contributes significantly to defining ECAD of printed circuit boards by leveraging historical design data and contextual information. Machine learning algorithms analyze past designs and user preferences, aiding in the creation of optimal ECAD specifications (Abrantes et al., 2017).

Signal allocation benefits from data science-driven optimization, where algorithms consider signal characteristics, historical allocation patterns, and design constraints to efficiently allocate signals to buses (Kwon et al., 2008).

In the development of electronic schematic designs, data science aids in automated suggestion of component placement, considering historical design layouts, signal flows, and optimal component arrangements (Pramerdorfer & Kampel, 2015).

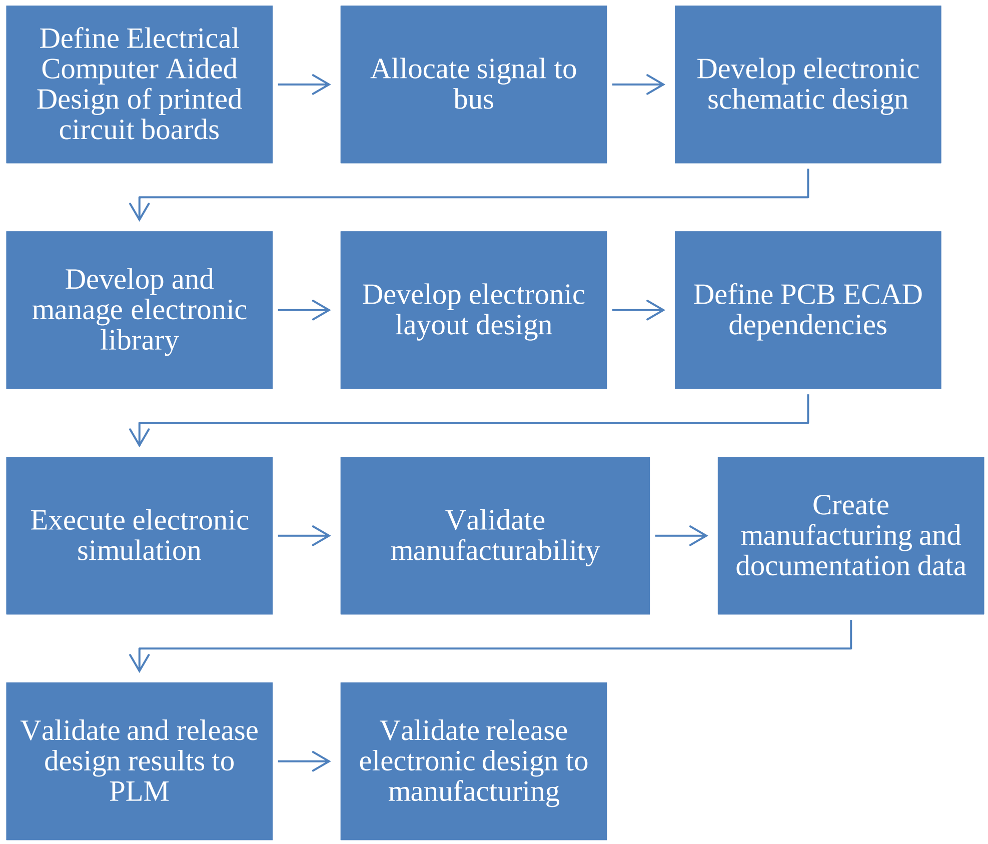

Figure 60 PCB Design Management Process Flow. Source: Author

The electronic library is efficiently managed through data-driven systems that employ Natural Language Processing (NLP) algorithms to catalog and categorize components. This ensures a comprehensive and organized electronic library (Chan & Chan, 2005).

Electronic layout design development benefits from predictive modeling, where data science algorithms analyze design parameters, past layout successes, and constraints to recommend optimal layout configurations (Huang et al., 2019).

Defining ECAD dependencies is enhanced by data science, automating the identification of interdependencies between different components or modules, ensuring a more robust and error-resistant design (Delaney & Phelan, 2009).

Electronic simulation execution is streamlined through data-driven simulation tools that analyze historical simulation data to optimize simulation parameters and predict potential issues before actual execution.

Manufacturability validation benefits from data science analytics that assess design parameters against manufacturing capabilities, predicting potential challenges, and ensuring that designs are manufacturable (Kwon et al., 2008).

Creating manufacturing and documentation data is optimized by data science systems that automate data generation, ensuring accuracy and completeness in manufacturing documentation.

Design release validation to PLM (Product Lifecycle Management) and manufacturing is facilitated through data-driven checks, verifying that designs align with standards and are ready for the next phases (Abrantes et al., 2017).

In summary, the infusion of data science into PCB Design Management activities within Electrical & Electronic Design introduces efficiencies and optimizations across the entire design lifecycle. Leveraging historical data, predictive modeling, and automated analytics, data science ensures the creation of robust and manufacturable PCB designs, contributing to the overall success of Product Design and Development (Abrantes et al., 2017; Chan & Chan, 2005; Delaney & Phelan, 2009; Huang et al., 2019; Kwon et al., 2008; Pramerdorfer & Kampel, 2015).

4.1.5.6 EE Component & Library Management

In the realm of Electrical and Electronics Component & Library Management, the integration of data science holds immense potential for revolutionizing key business processes as shown in *Figure 61* within a typical Electrical & Electronic Design function. One pivotal aspect lies in the definition of components, where integrated circuit design, interfaces, and electrical characteristics play a critical role. Data science can be instrumental in automating the analysis of vast datasets related to component specifications, enabling engineers to swiftly identify optimal components for specific design requirements. Machine learning algorithms can learn from historical component usage patterns, aiding in the prediction of potential component failures or the identification of more efficient alternatives.

A significant challenge in the contemporary design landscape is managing multi-site design and library collaboration. Data science solutions can facilitate seamless collaboration by analyzing data from multiple sites, identifying patterns, and streamlining the integration of design libraries across various locations. This not only enhances efficiency but also ensures a standardized approach to component and library management, fostering cohesion in the design process.

Library management and adherence to standards represent another critical facet of Electrical and Electronics Component Management. Data science applications can be employed to analyze and enforce compliance with industry standards, ensuring that design libraries are up-to-date and aligned with regulatory requirements. Additionally, predictive analytics can optimize library resources by anticipating changes in component availability or specifications, aiding in proactive decision-making.

Reviewing library design data is a fundamental step in maintaining the integrity of the design process. Here, data science techniques can enhance the accuracy and efficiency of the review process. Automated algorithms can sift through vast datasets, flagging discrepancies, and ensuring that design data aligns with established standards. This not only accelerates the review process but also minimizes the risk of errors in the final design, contributing to overall design quality.

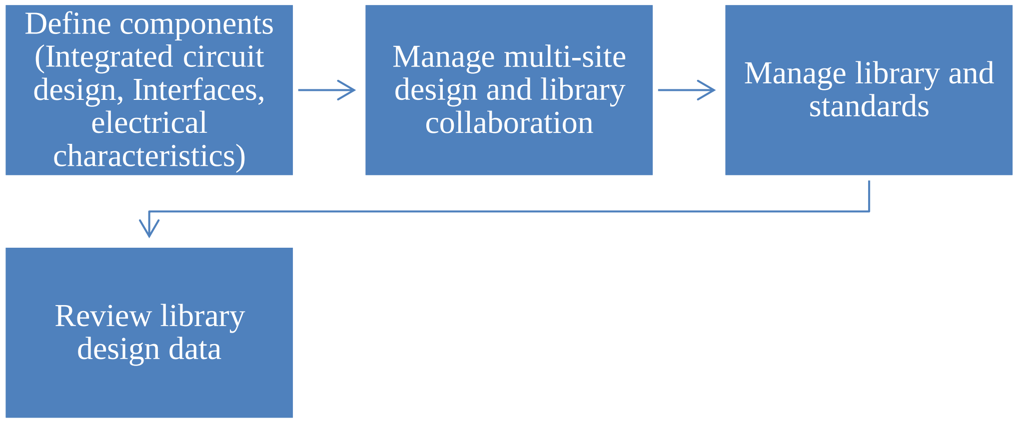

Figure 62 Electrical and Electronics Component and Libraray Management process flow. Source: Author

In summary, the infusion of data science into Electrical and Electronics Component & Library Management processes has the potential to elevate the efficiency, accuracy, and collaboration within a typical Electrical & Electronic Design function. From component definition to multi-site collaboration, library management, and design data review, data science emerges as a transformative force, empowering design teams to navigate the complexities of contemporary electrical and electronic design with enhanced precision and agility (Conti & Orcioni, 2019; Gil et al., 2020; Li et al., 2016; Ortiz et al., 2012; Tiedeken et al., 2013; Vorapojpisut, 2023).

4.1.5.7 Integrated Circuit Design

In the domain of Electrical & Electronic Design within the broader context of Product Design and Development, the integration of data science into EE Component & Library Management activities (shown in *Figure 63)* holds significant promise for improving efficiency and collaboration. This section explores how data science can be effectively applied to activities involving the definition of components, management of multi-site design and library collaboration, library and standards management, and the review of library design data.

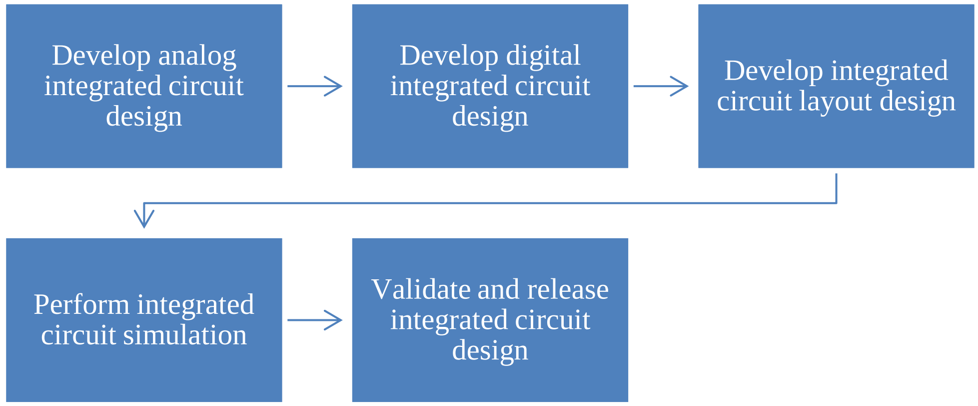

Figure 64 Integrated Circuit Design Process Flow. Source: Author

Define Components: Data science contributes to defining components by leveraging predictive modeling and analysis. Integrated circuit design, interfaces, and electrical characteristics can be optimized through machine learning algorithms that analyze historical design data, enabling engineers to make informed decisions based on previous successful designs (Pramerdorfer & Kampel, 2015).

Manage Multi-Site Design and Library Collaboration: Data science facilitates multi-site design collaboration by automating the analysis of design data across different locations. Predictive analytics models can identify patterns and dependencies in design processes, streamlining collaboration and ensuring consistency across multiple sites (Kwon et al., 2008).

Manage Library and Standards: In library and standards management, data science plays a key role in automating the categorization and organization of design components. Natural Language Processing (NLP) algorithms can process standards documentation, ensuring that libraries are compliant and aligned with industry regulations (Abrantes et al., 2017).

Review Library Design Data: Reviewing library design data is enhanced through data-driven tools. Machine learning models can assist in the automated evaluation of design data, identifying anomalies or deviations from standards. This objective review process contributes to the overall quality assurance of library design data (Chan & Chan, 2005).

In summary, the integration of data science into EE Component & Library Management activities within Electrical & Electronic Design offers significant benefits. From optimizing component definitions using predictive modeling to streamlining multi-site collaboration and ensuring compliance with standards, data science contributes to a more efficient and effective product design and development process. The utilization of advanced data science methodologies aligns with the contemporary trend of leveraging technology for enhanced decision-making in engineering design (Alexander & Styblinski, 1996; Mkrtchan et al., 2022; Padovani et al., 2007; Qiu, 2023).

4.1.5.8 Mitigation Strategies for Challenges in Adoption of Data Science

Below shown *Table 5*, outlines the data science use cases, maps them to business agility goals, identifies challenges, associated risks, and provides mitigation strategies.

Table 5 Data Science Use Cases for the various process in Electrical and Electronics Design function. Source : Author

Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
EE Architecture & Systems Design	Associate and Allocate Functions to Platform Design: Use historical data to optimize function-platform associations.	Lack of skilled workforce: Limited expertise in data science for function-platform optimization.	Suboptimal allocations, potential performance issues.	Provide training programs, collaborate with external experts, and invest in skill development.

Table 5 Data Science Use Cases for the various process in Electrical and Electronics Design function. Source : Author				
Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
EE Architecture & Systems Design	Create Electrical and Electronic Platform Architectures: Apply machine learning to predict optimal platform configurations.	Data quality and availability: Incomplete or unreliable platform design data.	Inaccurate predictions, compromised design integrity.	Implement data quality checks, invest in data cleansing tools, and establish data governance practices.
EE Architecture & Systems Design	Capture Electrical and Electronic Requirements and Constraints: Utilize NLP for automated extraction and analysis.	Integration with existing systems: Difficulty integrating NLP algorithms with current requirement systems.	Workflow disruptions, inconsistent requirement extraction.	Conduct thorough system compatibility assessments, work with IT teams to ensure seamless integration.
EE Architecture & Systems Design	Simulate, Calibrate, Conduct Verification and Validation: Enhance simulations with real-world data.	Privacy and security concerns: Protecting sensitive simulation data.	Unauthorized access, data breaches.	Implement robust encryption, access controls, and regular security audits.

Table 5 Data Science Use Cases for the various process in Electrical and Electronics Design function. Source : Author				
Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
EE Architecture & Systems Design	Evaluate and Optimize Electrical and Electronic Architecture: Use data science to evaluate multiple alternatives.	Scalability: Challenges in scaling evaluation algorithms for larger datasets.	Performance degradation, increased processing time.	Invest in scalable infrastructure, consider cloud-based solutions, and optimize algorithms for efficiency.
Electrical System Design using Generative Design	Define Design Rules: Automate identification based on historical data.	Lack of standardization: Inconsistencies in design rule definitions.	Inefficient design processes, potential errors.	Implement and enforce standardized procedures for design rules.
Electrical System Design using Generative Design	Perform Wiring Synthesis: Optimize wiring synthesis based on past designs.	Lack of skilled workforce: Insufficient knowledge in data science for wiring synthesis.	Inefficient synthesis, potential wiring issues.	Provide specialized training, collaborate with external experts, and invest in expertise.
Electrical System Design using Generative Design	Optimize Physical System Architecture: Use data-driven techniques to enhance physical architectures.	Privacy and security concerns: Protecting sensitive design data.	Unauthorized access, data breaches.	Implement robust encryption, access controls, and regular security audits.

Table 5 Data Science Use Cases for the various process in Electrical and Electronics Design function. Source : Author				
Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
Electrical Design Management	Breakdown System Constraints to Domain Level: Analyze complex relationships for domain-specific constraints.	Data quality and availability: Incomplete or unreliable constraint data.	Inaccurate domain-specific constraints, potential design flaws.	Implement data quality checks, invest in data cleansing tools, and establish data governance practices.
Electrical Design Management	Review Electrical Design: Utilize automated review algorithms based on historical data.	Integration with existing systems: Difficulty integrating review algorithms with current review processes.	Workflow disruptions, inconsistent reviews.	Conduct thorough system compatibility assessments, work with IT teams to ensure seamless integration.
Electrical Design Management	Route Cables, Validate, and Release Electrical Design: Optimize cable routing based on historical data.	Lack of skilled workforce: Limited expertise in data science for cable routing optimization.	Inefficient routing, potential cable issues.	Provide training programs, collaborate with external experts, and invest in skill development.

Table 5 Data Science Use Cases for the various process in Electrical and Electronics Design function. Source : Author				
Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
Electrical Harness Design	Execute Automated Parts Selection: Streamline parts selection based on historical usage patterns.	Lack of standardization: Inconsistencies in parts selection processes.	Inefficient selection, potential errors.	Implement and enforce standardized procedures for parts selection.
Electrical Harness Design	Perform Design Validation: Enhance validation using machine learning predictions.	Data quality and availability: Incomplete or unreliable validation data.	Inaccurate validation predictions, compromised harness integrity.	Implement data quality checks, invest in data cleansing tools, and establish data governance practices.
PCB Design Management	Develop Electronic Schematic Design: Optimize based on historical design data.	Scalability: Challenges in scaling design optimization for larger datasets.	Performance degradation, increased processing time.	Invest in scalable infrastructure, consider cloud-based solutions, and optimize algorithms for efficiency.
PCB Design Management	Validate Manufacturability: Predict manufacturability issues using historical manufacturing data.	Privacy and security concerns: Protecting sensitive design and manufacturing data.	Unauthorized access, data breaches.	Implement robust encryption, access controls, and regular security audits.

Table 5 Data Science Use Cases for the various process in Electrical and Electronics Design function. Source : Author				
Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
EE Component & Library Management	Define Components and Manage Library Collaboration: Recommend components based on historical data.	Lack of standardization: Inconsistencies in component definition and library collaboration.	Inefficient collaboration, potential errors.	Implement and enforce standardized procedures for component definition and library collaboration.
EE Component & Library Management	Develop Analog and Digital Integrated Circuit Design: Optimize based on historical data.	Lack of skilled workforce: Limited expertise in data science for integrated circuit design.	Inefficient design processes, potential errors.	Provide training programs, collaborate with external experts, and invest in skill development.
EE Component & Library Management	Perform Integrated Circuit Simulation: Enhance simulations with real-world data.	Integration with existing systems: Difficulty integrating simulation algorithms with current simulation processes.	Workflow disruptions, inconsistent simulations.	Conduct thorough system compatibility assessments, work with IT teams to ensure seamless integration.

Table 5, outlines the challenges, including a lack of skilled workforce, data quality issues, integration difficulties, privacy concerns, scalability challenges, misalignment with business objectives, and lack of standardization, pose potential risks. The associated risks include compromised design integrity, inaccurate predictions, workflow disruptions, and potential security breaches.

To mitigate these challenges and risks, organizations can adopt targeted strategies outlined in Table 5. These strategies include investing in workforce training, implementing data quality checks and governance practices, conducting thorough system compatibility assessments, addressing privacy and security concerns through encryption and access controls, investing in scalable infrastructure, and enforcing standardized procedures.

In conclusion, the systematic integration of data science use cases into Electrical & Electronic Design processes not only enhances efficiency and accuracy but also aligns with key business agility goals. Addressing challenges proactively and implementing effective mitigation strategies will ensure the successful adoption of data science in the Electrical & Electronic Design domain, fostering innovation and competitiveness.

4.1.6 Mitigation Strategies for Challenges in Adoption of Data Science in Software Design, Application Dev & SLM

The integration of data science in the domain of Software Design, Application Development, and Service Lifecycle Management (SLM) within the broader Product Design and Development organization holds significant potential for enhancing efficiency, decision-making, and overall software quality. This section explores how data science can be applied to the below activities within this function.

- Software Systems Architecture, Design & Integration
- Software Component Implementation
- Software Project Management

- Software Requirement Engineering
- Software Change & Configuration Management
- Software Build & Release Management
- Software Test & Quality Management
- Software Issues & Defect Management

4.1.6.1 Software Systems Architecture, Design & Integration

In the landscape of Software Systems Architecture, Design & Integration, the incorporation of data science holds the potential to revolutionize the Software Design, Application Development & SLM (Service Lifecycle Management) function within Product Design and Development organizations. This section explores how data science can be harnessed across activities as shown in *Figure 65* ranging from deriving software requirements to managing software configuration control.

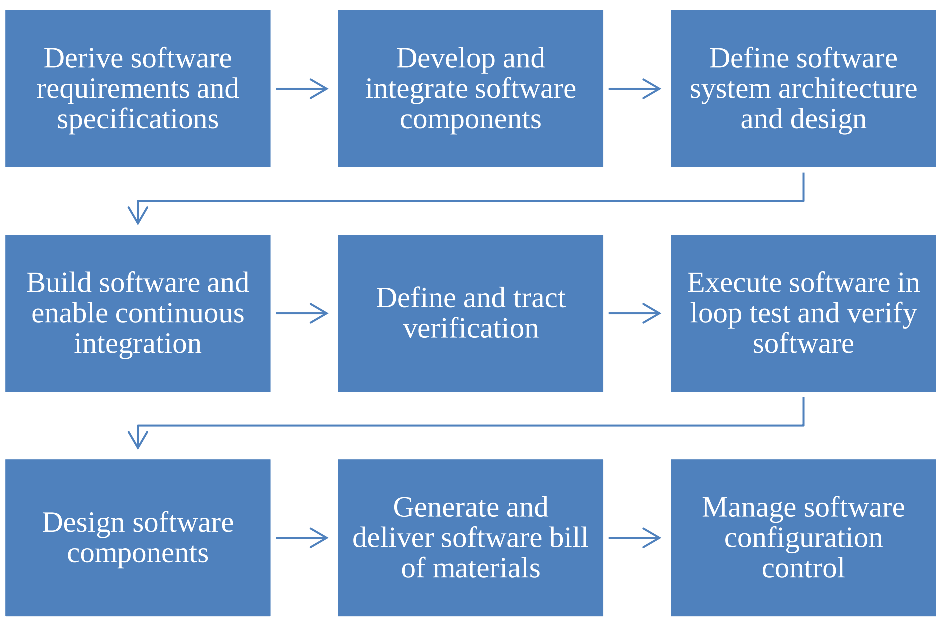

Figure 66 Software Systems Architecture, Design & Integration. Source: Author

Deriving software requirements and specifications benefits from data science's capability to analyze vast datasets and historical project information. By employing machine learning algorithms, patterns and trends in past requirements can be identified, aiding in the formulation of more accurate and comprehensive software specifications (Ebert et al., 2019; Mattmann et al., 2004).

Developing and integrating software components is streamlined through data-driven approaches that analyze compatibility, historical integration success, and coding practices. Machine learning models can assist in optimizing the integration process by identifying potential bottlenecks or areas prone to errors (Liu, 2019).

Defining software system architecture and design is enhanced by data science techniques such as predictive modeling. By analyzing historical architectural data and project constraints, machine learning can inform optimal architectural decisions, fostering more efficient and robust software designs (Marcus, 2010).

Building software and enabling continuous integration can benefit from predictive analytics to optimize build processes. Machine learning models can analyze historical build data to predict potential issues, allowing for proactive adjustments and minimizing integration challenges (Mattmann et al., 2011).

Defining and tracking verification processes can leverage data science to automate verification tracking. Machine learning algorithms can analyze verification data, providing insights into the effectiveness of testing processes and aiding in the identification of areas requiring additional verification efforts.

Executing software in loop tests and verifying software can be optimized through data-driven testing methodologies. Machine learning models can identify patterns in testing data, enabling more effective testing strategies and faster verification processes (Ebert et al., 2019).

Designing software components is facilitated by data science-driven approaches that analyze design patterns and historical component data. Machine learning can provide insights into optimal component design choices, ensuring that software components are well-crafted and adhere to industry best practices.

Generating and delivering software bill of materials can be automated using data science techniques. Machine learning algorithms can process software component data, ensuring accurate and up-to-date bill of materials generation for efficient delivery processes.

Managing software configuration control benefits from data-driven decision-making. Predictive analytics can assess the impact of proposed configuration changes, aiding in proactive identification of potential issues and ensuring a stable and controlled software configuration environment (Liu, 2019).

In summary, the infusion of data science into Software Design, Application Development & SLM activities offers a paradigm shift in how software systems are conceptualized, designed, and integrated. By leveraging historical data, predictive modeling, and machine learning algorithms, organizations can enhance decision-making, streamline processes, and foster continuous improvement throughout the software development lifecycle. This data-centric approach contributes to the creation of more robust, efficient, and reliable software systems (Ebert et al., 2019; Liu, 2019; Marcus, 2010; Mattmann et al., 2011).

4.1.6.2 Software Component Implementation

In the domain of Product Design and Development, specifically within the Software Design, Application Development, and Service Lifecycle Management (SLM) function, data science emerges as a key enabler for enhancing the Software Component Implementation process. This section explores the application of data science in various activities as shown in *Figure 67*, ranging from capturing software component specifications to generating and delivering software packages.

Capture Software Component Specifications and Trace to Derived Software Specifications: Data science aids in capturing software component specifications and tracing them to derived software specifications by employing natural language processing (NLP) algorithms. These algorithms analyze textual data from requirements documents and traceability matrices, ensuring that software specifications are accurately captured and aligned with derived specifications (Ali et al., 2018).

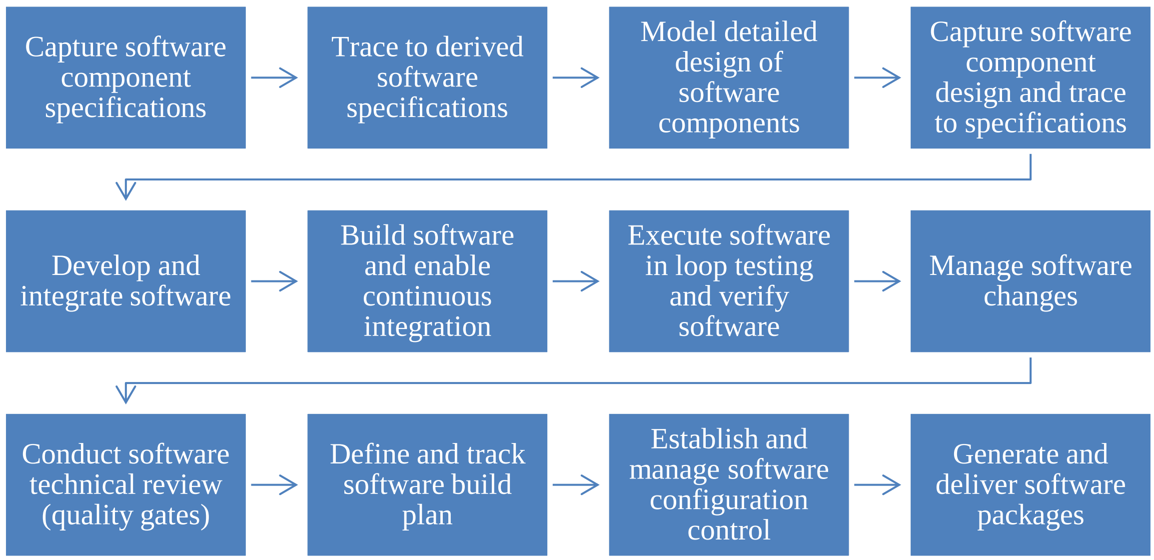

Figure 68 Software Component Implementation Process Flow. Source: Author

Model Detailed Design of Software Components: Data science contributes to the modeling of detailed design by employing machine learning models that analyze historical design data. These models assist in predicting optimal design patterns and structures, ensuring a more efficient and effective detailed design phase (Banerjee et al., 2015).

Capture Software Component Design and Trace to Specifications: NLP algorithms are utilized to capture software component design and establish traceability links to specifications. This ensures that the designed components align with the specified requirements, facilitating a more transparent and traceable design process (Bener et al., 2016).

Develop and Integrate Software: Data science plays a role in the development and integration of software by employing algorithms that optimize code generation and integration processes. Predictive analytics models can analyze historical data to suggest efficient coding practices and integration strategies, contributing to improved software development workflows (Dwivedi, 2020).

Build Software and Enable Continuous Integration: Automated build processes and continuous integration benefit from data science-driven systems. Machine learning algorithms can optimize build configurations and predict potential integration issues, ensuring a more seamless and continuous integration process (Rehioui, 2021).

Execute Software in Loop Testing and Verify Software: Data science facilitates loop testing and software verification by analyzing test data and predicting potential areas of failure. Machine learning models can assist in identifying critical test scenarios, optimizing the testing process, and improving software verification outcomes.

Manage Software Changes: Change management in software is enhanced through data-driven systems that analyze historical change data. Predictive analytics models can assist in prioritizing and managing software changes, ensuring a more efficient change management process.

Conduct Software Technical Review (Quality Gates): Automated technical reviews benefit from data science by employing algorithms that assess code quality against predefined criteria. These models can assist in conducting objective and consistent technical reviews, ensuring adherence to quality gates.

Define and Track Software Build Plan: Data science contributes to defining and tracking the software build plan by analyzing historical build data and predicting optimal build configurations. This ensures that the build plan is dynamically adapted based on project-specific requirements.

Establish and Manage Software Configuration Control: Software configuration control is optimized through data-driven systems that employ machine learning models. These models analyze configuration data to ensure that software versions are controlled, aligned with specifications, and compliant with established standards.

Generate and Deliver Software Packages: Data science facilitates the generation and delivery of software packages by optimizing packaging processes. Predictive analytics models can analyze packaging requirements, historical delivery data, and customer preferences to ensure the timely and accurate delivery of software packages.

In summary, the integration of data science into Software Component Implementation processes within the Software Design, Application Development, and SLM function significantly enhances efficiency and effectiveness. From capturing specifications to delivering software packages, data science contributes to more informed decision-making, streamlined workflows, and improved software quality in the product design and development lifecycle. This data-centric approach aligns with industry trends, emphasizing the role of data science in optimizing software engineering practices (Ali et al., 2018; Banerjee et al., 2015; Bener et al., 2016; Dwivedi, 2020; Rehioui, 2021).

4.1.6.3 Software Project Management

In the landscape of Software Design, Application Development, and Service Lifecycle Management (SLM) within the Product Design and Development domain, data science emerges as a key enabler for effective Software Project Management (SPM). This section explores the application of data science in activities as shown in *Figure 69*, such as identifying project resources, assigning resources, managing project progress, monitoring resource utilization, executing audits and metrics reviews, and generating reports and dashboards.

Identifying project resources benefits from data science through advanced analytics models that consider historical project data, resource skillsets, and project requirements. Predictive modeling, as proposed by Grabis et al. (2019), aids in foreseeing resource needs, ensuring optimal resource allocation and project planning.

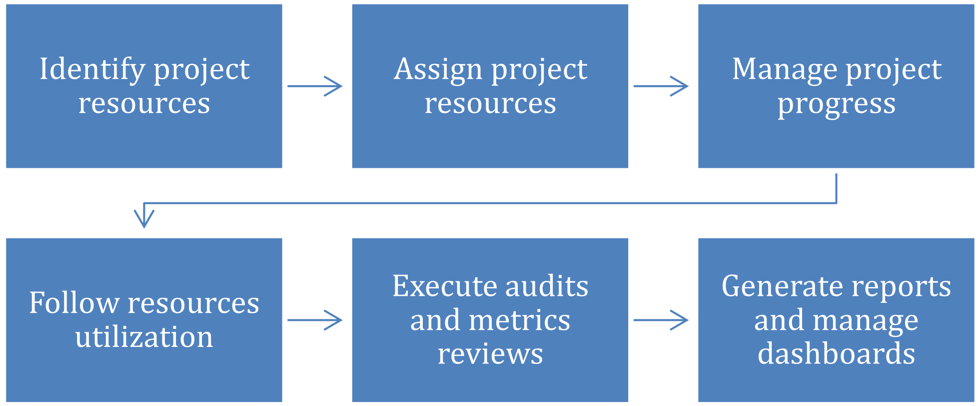

Figure 70 Software Project Management Source: Author

Assigning project resources is optimized by data science algorithms that consider resource availability, expertise, and workload. Advanced resource allocation models, as discussed by Haidabrus et al. (2021), leverage machine learning to align resources with project demands, balancing workloads for improved efficiency.

Managing project progress leverages data science to analyze project timelines, task dependencies, and resource contributions. Predictive analytics models, in alignment with Prasad et al. (2010), provide insights into potential bottlenecks and allow for proactive adjustments, ensuring project timelines are met.

Following resource utilization involves real-time monitoring using data science-driven dashboards. Yousef et al. (2006) advocate for the use of data analytics to track resource engagement, helping project managers identify underutilized or overloaded resources and make timely adjustments.

Executing audits and metrics reviews benefit from data science by automating the analysis of code repositories, project documentation, and development metrics. Machine learning models can identify patterns indicative of code quality issues or process inefficiencies, as highlighted by Grabis et al. (2019).

Generating reports and managing dashboards are streamlined through data visualization tools driven by data science. Dashboards, as discussed by Haidabrus et al. (2021), provide real-time insights into project metrics, allowing stakeholders to make informed decisions based on the latest data.

In summary, the integration of data science into Software Project Management activities enhances resource identification, allocation, progress management, resource utilization tracking, audits, and reporting. By leveraging predictive analytics, machine learning, and data visualization, organizations can optimize project outcomes and drive efficiency in software design and development (Grabis et al., 2019; Haidabrus et al., 2021; Prasad et al., 2010; Yousef et al., 2006).

4.1.6.4 Software Requirement Engineering

In the context of Software Requirement Engineering, the integration of data science within the Software Design, Application Development, and Service Lifecycle Management (SLM) functions, specifically within Product Design and Development organizations, presents opportunities for enhancing the efficiency and effectiveness of various activities. This section explores the application of data science in activities as shown in *Figure 71*, such as defining and documenting requirements, decomposing requirements, managing, and tracing requirements, collaborating, and exchanging, reviewing, and approving requirements, reusing requirements, and managing requirement variants.

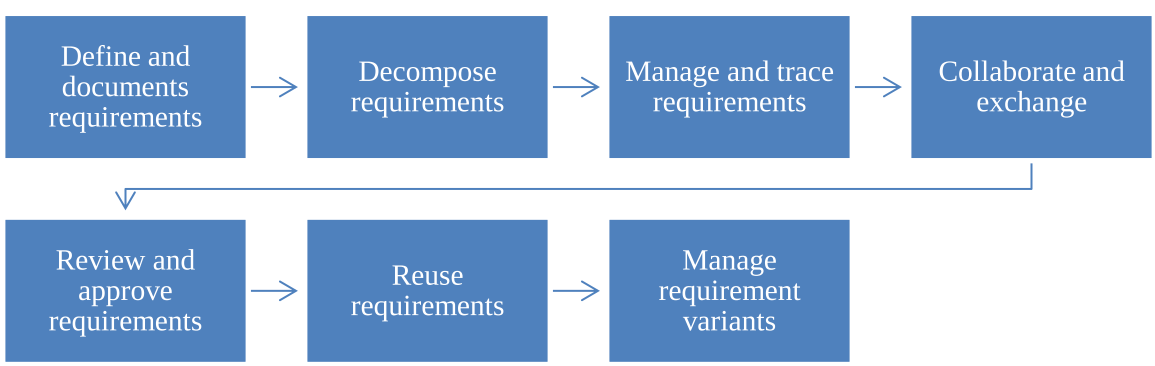

Figure 72 Software Requirement Engineering Process Flow. Source: Author

Data Science in Software Requirement Engineering:

Define and Document Requirements: Data science aids in the definition and documentation of requirements by leveraging Natural Language Processing (NLP) algorithms. These algorithms analyze textual data from various sources, helping automate the extraction and documentation of requirements in a structured manner (Altarturi et al., 2017).

Decompose Requirements: Machine learning techniques can be employed to predict optimal ways to decompose complex requirements. By analyzing historical project data, these models can assist in breaking down requirements into smaller, manageable components, improving overall project efficiency (Bakar et al., 2017).

Manage and Trace Requirements: Data science facilitates requirement management and tracing through the implementation of automated tools. These tools use algorithms to establish and track relationships between requirements, aiding in the seamless management and tracing of changes throughout the development lifecycle (Esteca et al., 2012).

Collaborate and Exchange: Collaborative filtering algorithms, inspired by recommendation systems, can enhance collaboration and information exchange among team members. By analyzing the preferences and interactions of team members, data science supports the targeted sharing of relevant requirement information (Maalej et al., 2016).

Review and Approve Requirements: Data science contributes to requirement reviews and approvals by implementing automated analysis tools. These tools can evaluate requirement documents against predefined criteria, ensuring consistency, completeness, and compliance with standards (Palomares, 2014).

Reuse Requirements: Predictive modeling, based on historical data, supports the identification and recommendation of reusable requirements. By analyzing successful past projects, data science enables organizations to identify patterns and reuse requirements that have proven effective in similar contexts (Altarturi et al., 2017).

Manage Requirement Variants: Data science assists in managing requirement variants by analyzing the relationships between different versions. By applying versioning algorithms, organizations can efficiently manage and track changes across multiple requirement variants, ensuring consistency and traceability (Bakar et al., 2017).

In summary, the integration of data science into Software Requirement Engineering activities within the Software Design, Application Development, and SLM functions provides innovative solutions to challenges in requirement definition, decomposition, management, collaboration, review, reuse, and variant management. Leveraging advanced algorithms and predictive modeling, organizations can enhance the entire software development lifecycle, promoting efficiency, collaboration, and the delivery of high-quality software products (Altarturi et al., 2017; Bakar et al., 2017; Esteca et al., 2012; Maalej et al., 2016; Palomares, 2014).

4.1.6.5 Software Change & Configuration Management

In the intricate landscape of Software Design, Application Development, and Service Lifecycle Management (SLM) within the Product Design and Development organization, the integration of data science into Software Change & Configuration Management is crucial. This section explores how data science can be applied to activities as shown in *Figure 73***,** involving the proposal and analysis of change, authorization of change, implementation of change, verification of implemented change, and the release and closure of change requests.

Proposing and Analyzing Change: Data science contributes to change proposals by analyzing historical project data and identifying patterns, risks, and potential impacts. Machine learning models, as suggested by Bartusevics et al. (2014), can assist in predicting the success of proposed changes based on similarities with past successful changes.

Authorizing Change: Authorization of change benefits from data science-driven decision-making. Machine learning algorithms, as discussed by S. Huang and Lo (2007), can assess the potential risks and benefits associated with change requests, aiding decision-makers in the authorization process.

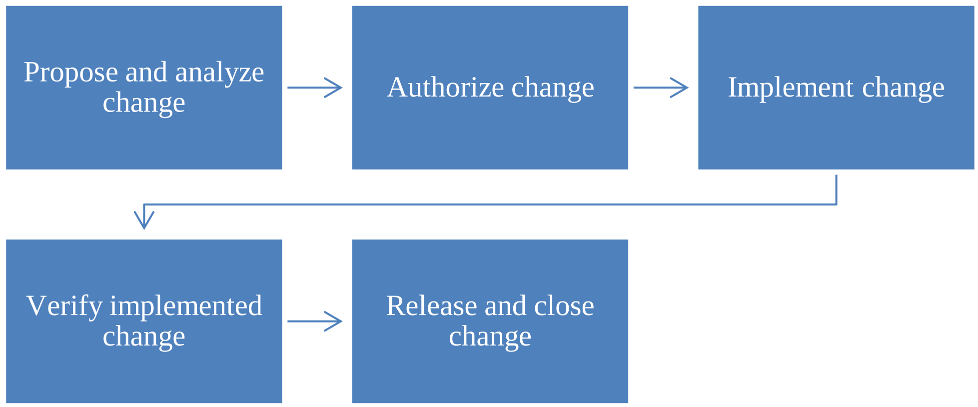

Figure 74 Typical Software Change & Configuration Management Process Flow. Source: Author

Implementing Change: Data science plays a vital role in the implementation of change by optimizing resource allocation and project planning. Mohan et al. (2008) highlights the application of predictive analytics to analyze project parameters, historical implementation data, and resource availability, providing insights into the optimal implementation approach.

Verifying Implemented Change: Verification of implemented changes is facilitated by data science through automated testing and validation processes. Xing (2010) suggests the use of machine learning models to predict potential issues in the verification phase, ensuring that changes align with specified standards and requirements.

Releasing and Closing Change: The release and closure of change requests benefit from data science-driven analytics. Predictive analytics models can assess the readiness of changes for release, considering factors such as code quality and testing outcomes. This ensures that only validated and high-quality changes are released, aligning with the principles discussed by Bartusevics et al. (2014).

In conclusion, the integration of data science into Software Change & Configuration Management within the context of Software Design, Application Development, and SLM brings forth advancements in change proposal analysis, authorization decision-making, implementation optimization, verification automation, and release decision support. This data-centric approach aligns with established research (Bartusevics et al., 2014; Huang & Lo, 2007; Mohan et al., 2008; Xing, 2010), contributing to the efficiency and effectiveness of software development processes.

4.1.6.6 Software Build & Release Management

In the realm of Product Design and Development, the integration of data science into Software Build & Release Management processes within the broader Software Design, Application Development & SLM function holds promise for improved efficiency and decision-making. This section explores the application of data science in activities as shown in *Figure 75*, such as defining product content to specification, managing product content and traceability, documenting product branches and content, managing product variants, managing product builds, and managing product releases.

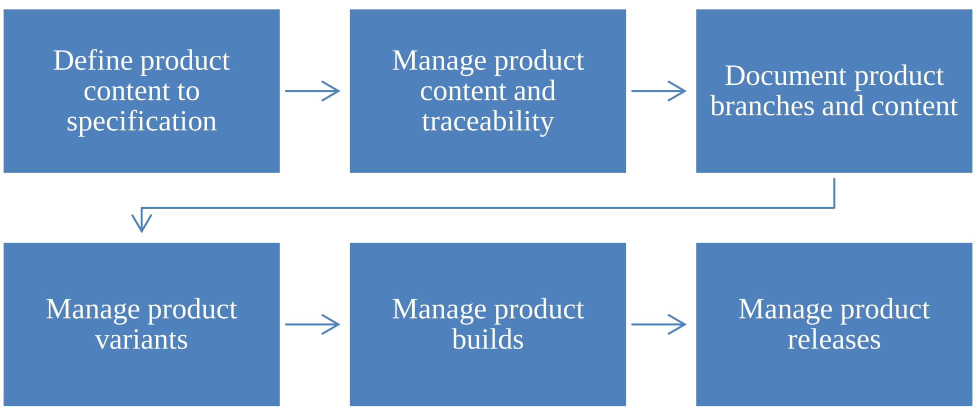

Figure 76 Typical Software Build & Release Management Process Flow. Source: Author

Data Science in Software Build & Release Management:

Data science enhances the definition of product content by analyzing historical product data and specifications. Machine learning algorithms can identify patterns and correlations, ensuring that the defined content aligns with past successful product configurations (Bagriyanik & Karahoca, 2016).

Managing product content and traceability benefits from data-driven traceability models. These models can analyze complex relationships within product content, providing insights into dependencies and facilitating more accurate tracking of changes and updates (Fernández & Angarita, 2018).

Documenting product branches and content is streamlined through automated systems driven by data science. Natural Language Processing (NLP) algorithms can process documentation, extracting relevant information, and ensuring comprehensive documentation of product branches and content (Jagtiani et al., 2018).

Data science contributes to managing product variants by optimizing the variant configuration process. Machine learning models can analyze historical variant data, market trends, and customer preferences to suggest optimal variant configurations, ensuring alignment with market demands (Souza et al., 2015).

Managing product builds is facilitated by data science-driven systems that optimize resource allocation and project planning. Predictive analytics models can analyze build parameters, historical build data, and resource availability to provide insights into the optimal build processes (Bird et al., 2015).

Managing product releases benefits from automated release management systems powered by data science. These systems can analyze release data, customer feedback, and historical release performance to optimize the release process, ensuring high-quality software delivery (Sassenburg, 2006).

In conclusion, the infusion of data science into Software Build & Release Management activities within the Software Design, Application Development & SLM function contributes to more informed decision-making and streamlined processes. This data-centric approach fosters efficient product content definition, precise traceability, comprehensive documentation, optimized variant management, resource-efficient builds, and successful product releases, ultimately enhancing the overall software development lifecycle

(Bagriyanik & Karahoca, 2016; Bird et al., 2015; Fernández & Angarita, 2018; Jagtiani et al., 2018; Sassenburg, 2006; Souza et al., 2015).

4.1.6.7 Software Test & Quality Management

In the landscape of Product Design and Development, specifically within the Software Design, Application Development & SLM function, the integration of data science into Software Test & Quality Management processes holds significant potential. This section explores how data science methodologies can be applied to activities as shown in *Figure 77*, related to planning, defining, executing, managing, evaluating, and reporting in software testing and quality management.

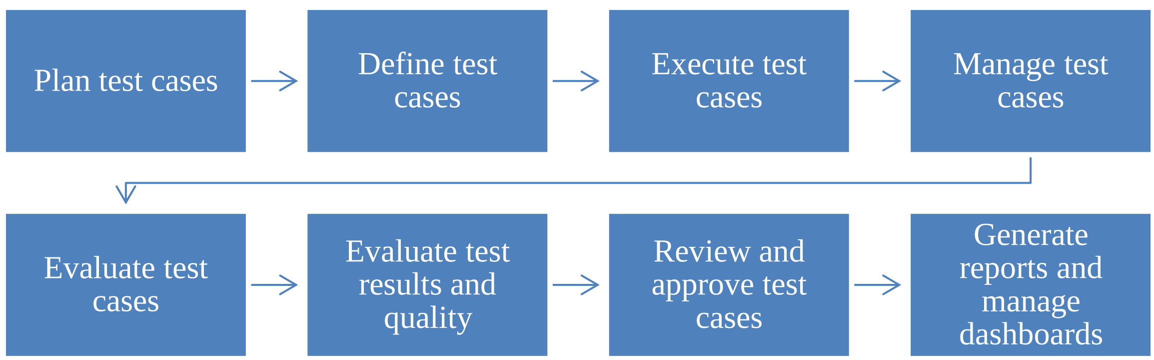

Figure 78 Typical Software Test & Quality Management function. Source: Author

Data Science in Software Test & Quality Management:

Data science plays a crucial role in planning test cases by analyzing historical data and project parameters. Predictive analytics models, informed by past project outcomes, contribute to more accurate test case planning, resource allocation, and risk mitigation (Martinez-Fernandez et al., 2019).

Defining test cases benefits from data-driven insights. Natural Language Processing (NLP) algorithms can analyze requirements documentation and historical test cases, facilitating the automated generation and optimization of comprehensive and precise test case definitions (Hewett, 2011).

Execution of test cases is optimized through data science-driven automation. Machine learning algorithms can identify patterns in code changes and select the most relevant test cases for automated execution, reducing manual effort and increasing test coverage (Valverde et al., 2014).

Managing test cases is streamlined through the application of data science to prioritize and organize test cases. Machine learning algorithms can dynamically categorize test cases based on historical defect data and project priorities, ensuring efficient resource utilization (Fernández & Angarita, 2018).

Evaluation of test cases is enhanced by data science, which enables automated analysis of test results. Predictive modeling can identify anomalies, assess the impact of defects, and recommend adjustments to test cases in real-time, improving the overall testing process (Jung, 2015).

Review and approval of test cases benefit from data-driven decision support systems. Predictive analytics models can assess the completeness and effectiveness of test cases, aiding reviewers in making informed decisions and reducing the risk of overlooking critical aspects (Fernández & Angarita, 2018).

Generating reports and managing dashboards are optimized through data science-driven analytics. Visualization tools powered by machine learning algorithms can provide real-time insights into test results, quality metrics, and project progress, facilitating data-driven decision-making and communication (Hewett, 2011).

In summary, the infusion of data science into Software Test & Quality Management activities within Software Design, Application Development & SLM function contributes to more accurate planning, efficient execution, and improved evaluation of test cases. This data-centric approach aligns with the evolving landscape of software development, promoting enhanced efficiency and quality throughout the product development lifecycle (Fernández & Angarita, 2018; Hewett, 2011; Jung, 2015; Martinez-Fernandez et al., 2019; Valverde et al., 2014).

4.1.6.8 Software Issues & Defect Management

In the realm of Software Design, Application Development, and Service Lifecycle Management (SLM) within the broader context of Product Design and Development, the incorporation of data science into Software Issues & Defect Management processes as shown in *Figure 79***,** holds the potential for enhanced issue identification, resolution, and overall software quality improvement.

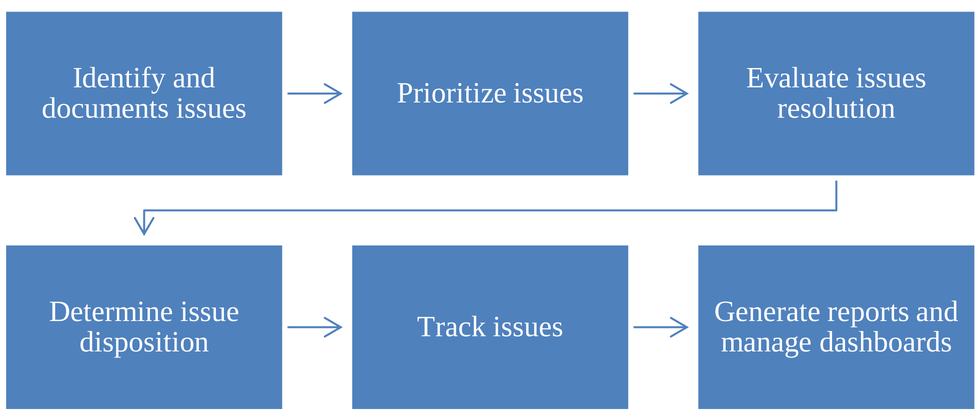

Figure 80 Typical Software Issues & Defect Management Process Flow. Source: Author

Identifying and Documenting Issues: Data science, as proposed by Adak (2018) and Yuan Chen et al. (2010), can automate the identification and documentation of software issues. Machine learning algorithms can analyze historical issue data, code repositories, and user feedback to proactively identify potential issues, contributing to a more comprehensive understanding of software challenges.

Prioritizing Issues: Ceylan et al. (2006) and Hewett (2011) emphasize the importance of effective issue prioritization. Data science enables automated prioritization by considering factors such as severity, impact on users, and historical issue resolution times. This ensures that resources are allocated efficiently to address critical issues first.

Evaluating Issues Resolution: Kaur (2013) and Periasamy & Mishbahulhuda (2017) highlight the significance of evaluating issue resolution strategies. Data science-driven analytics can assess the effectiveness of different resolution approaches by analyzing historical data on issue resolution times, success rates, and user satisfaction.

Determining Issue Disposition: Punitha & Chitra (2013) emphasize the need for a systematic approach to determining issue disposition. Data science supports this by developing decision models that consider factors like issue complexity, available resources, and organizational priorities to guide informed decisions on issue disposition.

Tracking Issues: Data science plays a crucial role in real-time issue tracking. Automated tracking systems, supported by machine learning models, can monitor issue progress, predict potential delays, and alert stakeholders to deviations from expected timelines. This facilitates proactive management and timely resolution.

Generating Reports and Managing Dashboards: Yuan et al. (2010) advocate for comprehensive reporting and dashboard management. Data science facilitates the generation of insightful reports by analyzing issue data trends, resolution times, and user feedback. Interactive dashboards provide stakeholders with real-time visibility into the software's issue landscape.

In conclusion, the integration of data science into Software Issues & Defect Management within Software Design, Application Development, and SLM processes enhances the identification, prioritization, evaluation, disposition, tracking, and reporting of software issues. By leveraging historical data and advanced analytics, organizations can foster a more proactive and data-driven approach to improving software quality and addressing challenges throughout the product development lifecycle (Adak, 2018; Ceylan et al., 2006;

Hewett, 2011; Kaur, 2013; Periasamy & Mishbahulhuda, 2017; Punitha & Chitra, 2013; Yuan Chen et al., 2010).

4.1.6.9 Mitigation Strategies for Challenges in Adoption of Data Science

In the realm of Software Systems Architecture, Design, and Integration, the integration of data science and AI manifests across various crucial stages and challenges. Table 6 summarizes the different data science use cases in this domain, associated challenges and risk along with the proposed mitigation strategies that can be taken by organizations. Below is a discussion on the key factors outlined in Table 6. Leveraging Natural Language Processing (NLP) in the initial process involves deriving software requirements and specifications with unprecedented efficiency. NLP algorithms assist in extracting and understanding requirements, significantly reducing the margin for errors and misinterpretations. This not only aligns with the business agility goal of improving behavioral awareness but also streamlines the subsequent design phases.

Table 6 Data Science Use Cases for the various process in Software Systems Architecture, Design, and Integration sub function. Source : Author

Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Derive Software Requirements and Specifications: NLP for efficient requirement extraction.	Improve Behavioral Awareness, Enable Augmented Decision Making	Lack of skilled workforce: Insufficient expertise in NLP.	Inaccurate requirements extraction.	Provide training programs, collaborate with experts.
Develop and Integrate Software Components:	Create Dynamic Processes	Data quality and availability:	Integration errors, conflicts.	Implement data quality checks, invest

Table 6 Data Science Use Cases for the various process in Software Systems Architecture, Design, and Integration sub function. Source : Author

Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Automation of integration using machine learning.	for Fast Execution	Incomplete integration data.		in data cleansing.
Define Software System Architecture and Design: ML for optimal architecture suggestions.	Enable Augmented Decision Making	Integration with existing systems: Difficulty in integrating ML algorithms.	Workflow disruptions, inconsistent designs.	Conduct system compatibility assessments, work with IT teams.
Build Software and Enable Continuous Integration: Data-driven optimization of the build process.	Create Dynamic Resources for Fast Execution	Privacy and security concerns: Protecting sensitive build data.	Unauthorized access, data breaches.	Implement robust encryption, access controls.
Define and Track Verification: Predictive analytics for proactive tracking and resolution.	Enable Augmented Decision Making	Scalability: Challenges in scaling verification algorithms.	Performance degradation, increased processing time.	Invest in scalable infrastructure, consider cloud solutions.

Table 6 Data Science Use Cases for the various process in Software Systems Architecture, Design, and Integration sub function. Source : Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Execute Software in Loop Test and Verify Software: Automated testing guided by machine learning.	Enable Augmented Decision Making, Create Dynamic Resources for Fast Execution	Alignment with business objectives: Misalignment with testing goals.	Ineffective testing, compromised software quality.	Regularly align testing objectives with business goals.
Design Software Components: Data-driven design recommendations.	Enable Augmented Decision Making	Lack of standardization: Inconsistencies in design processes.	Inefficient designs, potential errors.	Implement standardized design procedures.
Generate and Deliver Software Bill of Materials: Automated generation based on dependency analysis.	Create Dynamic Processes for Fast Execution	Lack of skilled workforce: Limited expertise in dependency analysis.	Inaccurate documentation, potential errors.	Provide training programs, collaborate with experts.
Manage Software Configuration Control: Optimization of configuration	Create Dynamic Resources for Fast Execution	Data quality and availability: Incomplete or unreliable	Inaccurate configuration management.	Implement data quality checks, invest in data cleansing.

Table 6 Data Science Use Cases for the various process in Software Systems Architecture, Design, and Integration sub function. Source : Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
control using machine learning.		configuration data.		

Moving forward, the development and integration of software components benefit from automation guided by machine learning. This dynamic process enhances the creation of a cohesive software system, contributing to the goal of creating dynamic processes for fast execution. The integration process, when informed by machine learning insights, minimizes errors, conflicts, and inefficiencies, ensuring a smoother development trajectory. The definition of the software system architecture and design is another critical phase where machine learning comes into play. ML algorithms can analyze historical patterns, suggesting optimal architecture solutions. This aligns with the business agility goal of enabling augmented decision-making, empowering architects with data-driven insights for more informed design choices. Privacy and security concerns are addressed through robust encryption and access controls, safeguarding sensitive design data. Ensuring compatibility with existing systems is a key challenge, and compatibility assessments, in collaboration with IT teams, serve as a mitigation strategy. Scalability, a common challenge in integrating AI, is managed by investing in scalable infrastructure and considering cloud solutions. This not only addresses the scalability challenge but also contributes to the goal of creating dynamic resources for fast execution.

Software Component Implementation: The Software Component Implementation process is revolutionized by AI use cases, bringing efficiency and precision to each stage. Table 7 summarizes the different data science use cases in this domain, associated challenges and risk along with the proposed mitigation strategies that can be taken by organizations.

Beginning with the capture of software component specifications, NLP takes center stage, ensuring accurate extraction and documentation. This aligns with the business agility goal of improving behavioral awareness, as it enhances the clarity and accuracy of specifications. Machine learning algorithms play a pivotal role in tracing software components to derived specifications, optimizing the traceability process. This, in turn, contributes to the business agility goal of creating dynamic resources for fast execution. The elimination of inefficiencies and inaccuracies in tracing data ensures a seamless implementation process. Detailed design modeling of software components benefits from machine learning insights, optimizing models based on historical patterns. This aligns with the business agility goal of enabling augmented decision-making, providing designers with data-driven recommendations for more efficient models. Like the previous process, privacy and security concerns are addressed through robust encryption and access controls, protecting sensitive design data. Integration challenges are mitigated through collaboration with IT teams, ensuring a smooth integration of machine learning algorithms into existing systems. Scalability is managed by investing in scalable infrastructure and considering cloud solutions, providing a foundation for creating dynamic resources for fast execution. By addressing these challenges, organizations can fully capitalize on the potential of AI in Software Component Implementation, enhancing both efficiency and agility in the software development life cycle.

Table 7 Data Science Use Cases, Challenges & Mitigation Strategies for the various process in Software Component Implementation. Source : Author

Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Capture Software Component Specifications: NLP for accurate specification extraction.	Improve Behavioral Awareness, Enable Augmented Decision Making	Lack of skilled workforce: Insufficient expertise in NLP.	Inaccurate specifications, potential errors.	Provide training programs, collaborate with experts.

Table 7 Data Science Use Cases, Challenges & Mitigation Strategies for the various process in Software Component Implementation. Source : Author

Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Trace to Derived Software Specifications: Data-driven tracing mechanisms for automated connection.	Enable Augmented Decision Making, Create Dynamic Resources for Fast Execution	Data quality and availability: Incomplete tracing data.	Tracing errors, potential issues.	Implement data quality checks, invest in data cleansing.
Model Detailed Design of Software Components: ML for efficient modeling based on historical patterns.	Enable Augmented Decision Making	Integration with existing systems: Difficulty in integrating ML algorithms.	Workflow disruptions, inconsistent models.	Conduct system compatibility assessments, work with IT teams.
Capture Software Component Design and Trace to Specifications: Automation of the design traceability process.	Enable Augmented Decision Making	Privacy and security concerns: Protecting sensitive design data.	Unauthorized access, data breaches.	Implement robust encryption, access controls.
Develop and Integrate Software: Continuous integration facilitated by machine learning algorithms.	Create Dynamic Processes for Fast Execution	Scalability: Challenges in scaling integration algorithms.	Performance degradation, increased processing time.	Invest in scalable infrastructure, consider cloud solutions.

Table 7 Data Science Use Cases, Challenges & Mitigation Strategies for the various process in Software Component Implementation. Source : Author

Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Build Software and Enable Continuous Integration: Optimization of the build process using data-driven insights.	Create Dynamic Resources for Fast Execution	Alignment with business objectives: Misalignment with build goals.	Inefficient build processes, potential errors.	Regularly align build objectives with business goals.
Execute Software in Loop Testing and Verify Software: Automated testing guided by machine learning.	Enable Augmented Decision Making, Create Dynamic Resources for Fast Execution	Lack of standardization: Inconsistencies in testing processes.	Inefficient testing, compromised software quality.	Implement standardized testing procedures.
Manage Software Changes: Data-driven change management for efficient handling of changes.	Create Dynamic Processes for Fast Execution	Data quality and availability: Incomplete or unreliable change data.	Inaccurate change management, potential errors.	Implement data quality checks, invest in data cleansing.

Software Project Management: In the realm of Software Project Management, the infusion of AI brings a paradigm shift in resource allocation, progress tracking, and overall project efficiency. Table 8 summarizes the different data science use cases in this domain, associated challenges and risk along with the proposed mitigation strategies that can be taken by organizations. The identification of project resources is expedited with data-driven insights, contributing to the creation of dynamic resources for fast execution.

Machine learning algorithms optimize the assignment of resources, aligning with the business agility goal of creating a flexible and responsive workforce.

Real-time tracking of project progress is crucial for effective decision-making. Data-driven tracking mechanisms offer a comprehensive overview, promoting improved behavioral awareness among project stakeholders. Additionally, the goal of creating dynamic resources for fast execution is furthered as AI enhances the monitoring and optimization of resource utilization based on historical patterns.

Table 8 Data Science Use Cases for the various process in Software Project Management sub function. Source : Author

Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Identify Project Resources: Data-driven insights for efficient resource identification.	Create Dynamic Resources for Fast Execution	Lack of skilled workforce: Limited expertise in resource allocation.	Inefficient resource allocation, potential delays.	Provide training programs, collaborate with experts.
Assign Project Resources: Optimization of resource assignments using machine learning.	Create Dynamic Resources for Fast Execution	Data quality and availability: Incomplete or unreliable resource data.	Suboptimal resource assignments, potential inefficiencies.	Implement data quality checks, invest in data cleansing.
Manage Project Progress: Real-time insights into project	Enable Augmented Decision Making	Privacy and security concerns: Protecting	Unauthorized access, data breaches.	Implement robust encryption, access controls.

Table 8 Data Science Use Cases for the various process in Software Project Management sub function. Source : Author

Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
progress using data-driven tracking.		sensitive project data.		
Follow Resources Utilization: Monitoring and optimization of resource utilization based on historical patterns.	Create Dynamic Resources for Fast Execution	Scalability: Challenges in scaling resource utilization algorithms.	Performance degradation, increased processing time.	Invest in scalable infrastructure, consider cloud solutions.
Execute Audits and Metrics Reviews: Automated audits and metric reviews guided by data science.	Improve Behavioral Awareness	Alignment with business objectives: Misalignment with audit goals.	Ineffective audits, potential compliance issues.	Regularly align audit objectives with business goals.
Generate Reports and Manage Dashboards: Data-driven reporting and	Create Dynamic Resources for Fast Execution	Lack of standardization: Inconsistencies in reporting processes.	Inefficient reporting, potential errors.	Implement standardized reporting procedures.

Table 8 Data Science Use Cases for the various process in Software Project Management sub function. Source : Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
dashboard management for dynamic insights.				

Audits and metrics reviews, traditionally time-consuming, can benefit immensely from automated processes guided by data science. This not only aligns with the business agility goal of improving behavioral awareness but also streamlines the auditing process, reducing the risk of oversight and errors.

While navigating these advancements, privacy and security concerns are paramount. Robust encryption and access controls ensure the protection of sensitive project data. Scalability challenges are addressed through strategic investments in scalable infrastructure, aligning with the business agility goal of creating dynamic resources for fast execution.

By embracing AI in Software Project Management, organizations empower themselves with the ability to respond dynamically to changing project dynamics, fostering a more agile and efficient project management ecosystem.

Software Requirement Engineering: In Software Requirement Engineering, AI introduces transformative capabilities in the definition, management, and reuse of requirements. Table 9 summarizes the different data science use cases in this domain, associated challenges and risk along with the proposed mitigation strategies that can be taken by organizations. Natural Language Processing (NLP) takes the lead in defining and documenting requirements, improving behavioral awareness by facilitating clearer and more accurate requirement extraction. The goal of enabling augmented decision-making is advanced as NLP algorithms streamline the requirement documentation process, reducing the risk of misinterpretations.

Table 9 Data Science Use Cases for the various process in Software Requirement Engineering sub function. Source: Author

Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Define and Document Requirements: NLP for efficient requirement definition and documentation.	Improve Behavioral Awareness, Enable Augmented Decision Making	Lack of skilled workforce: Insufficient expertise in NLP.	Inaccurate documentation, potential errors.	Provide training programs, collaborate with experts.
Decompose Requirements: Data-driven decomposition for efficient breakdown based on historical patterns.	Create Dynamic Processes for Fast Execution	Data quality and availability: Incomplete or unreliable decomposition data.	Inefficient decomposition, potential errors.	Implement data quality checks, invest in data cleansing.
Manage and Trace Requirements: Automated tracing mechanisms for	Enable Augmented Decision Making	Integration with existing systems: Difficulty in integrating tracing algorithms.	Workflow disruptions, inconsistent tracking.	Conduct system compatibility assessments, work with IT teams.

Table 9 Data Science Use Cases for the various process in Software Requirement Engineering sub function. Source: Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
accurate tracking and validation.				
Collaborate and Exchange: Data-driven collaboration tools for efficient communication and collaboration.	Enable Inclusive Decision Making	Privacy and security concerns: Protecting sensitive collaboration data.	Unauthorized access, data breaches.	Implement robust encryption, access controls.
Review and Approve Requirements: Automated review mechanisms guided by data science.	Enable Inclusive Decision Making	Scalability: Challenges in scaling review algorithms.	Performance degradation, increased processing time.	Invest in scalable infrastructure, consider cloud solutions.
Reuse Requirements: Data-driven insights for efficient	Enable Augmented Decision Making	Alignment with business objectives: Misalignment with reuse goals.	Inefficient reuse, potential errors.	Regularly align reuse objectives with business goals.

Table 9 Data Science Use Cases for the various process in Software Requirement Engineering sub function. Source: Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
identification and reuse of requirements.				
Manage Requirement Variants: Machine learning for streamlined management of requirement variants.	Enable Augmented Decision Making	Lack of standardization: Inconsistencies in variant management processes.	Inefficient variant management, potential conflicts.	Implement standardized variant management procedures.

Data-driven decomposition of requirements contributes to creating dynamic processes for fast execution. Machine learning algorithms, informed by historical patterns, optimize the breakdown of requirements, ensuring a more efficient and streamlined decomposition process.

Tracing and managing requirements are critical aspects of requirement engineering. Automated tracing mechanisms, guided by data science, enhance accuracy and tracking efficiency. This aligns with the business agility goal of creating dynamic resources for fast execution by minimizing errors and improving overall requirement traceability.

Collaboration and exchange of requirements are facilitated by data-driven collaboration tools, enabling inclusive decision-making. Privacy and security concerns are addressed through robust encryption and access controls, securing sensitive collaboration data.

Automation of the review and approval process, guided by data science, ensures not only efficient reviews but also adherence to standardization goals. This aligns with the business agility goal of creating dynamic processes for fast execution by streamlining the approval workflow.

In addressing challenges related to AI integration, organizations must prioritize training programs and collaboration with experts to overcome the lack of skilled workforce. Implementing data quality checks and investing in data cleansing strategies mitigate challenges related to data quality and availability.

By harnessing AI in Software Requirement Engineering, organizations can elevate the precision, speed, and collaboration aspects of the requirement management process, thereby enhancing overall business agility.

Software Change & Configuration Management undergoes a transformative shift with the integration of AI, streamlining change processes and enhancing overall efficiency. The proposal and analysis of change are expedited through data-driven analysis, aligning with the goal of enabling augmented decision-making. Machine learning algorithms analyze historical data to provide insights into the impact of proposed changes, reducing the risk of errors and ensuring a more informed decision-making process.

Authorization of change, a critical step in the change management process, is automated based on historical authorization patterns. This not only contributes to enabling augmented decision-making but also aligns with the goal of creating dynamic processes for fast execution by optimizing the authorization workflow.

Change implementation benefits from the optimization brought by machine learning algorithms. These algorithms ensure a smoother and more efficient implementation process, reducing the risk of errors and facilitating a faster execution of changes. Privacy and security concerns are addressed through robust encryption and access controls, safeguarding sensitive change-related data.

Automated verification of implemented changes further enhances the overall change management process. Machine learning algorithms analyze historical data to predict and verify the impact of changes, reducing the risk of overlooking potential issues. This aligns with the goal of creating dynamic processes for fast execution by streamlining the verification process.

Release and closure of changes are guided by data-driven insights, ensuring a more efficient and accurate process based on historical patterns. Regular alignment of release objectives with business goals mitigates risks related to misalignment with business objectives, contributing to the goal of creating dynamic processes for fast execution.

Addressing challenges associated with AI integration, organizations must provide training programs and collaborate with experts to overcome the lack of a skilled workforce. Implementing data quality checks and investing in data cleansing strategies mitigate challenges related to data quality and availability.

Incorporating AI into Software Change & Configuration Management establishes a foundation for a more agile and responsive change management process, allowing organizations to adapt to evolving requirements with enhanced efficiency. Table 10 summarizes the different data science use cases in this domain, associated challenges and risk along with the proposed mitigation strategies that can be taken by organizations.

Table 10 Data Science Use Cases for the various process in Software Change & Configuration Management sub function. Source : Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Propose and Analyze Change: Data-driven analysis for efficient change proposal and impact assessment.	Enable Augmented Decision Making	Lack of skilled workforce: Limited expertise in change analysis.	Inaccurate analysis, potential errors.	Provide training programs, collaborate with experts.
Authorize Change: Automated authorization based on historical authorization patterns.	Enable Augmented Decision Making	Data quality and availability: Incomplete or unreliable authorization data.	Inefficient authorization, potential risks.	Implement data quality checks, invest in data cleansing.
Implement Change: Optimization of the change implementation process using machine learning.	Create Dynamic Processes for Fast Execution	Privacy and security concerns: Protecting sensitive change data.	Unauthorized access, data breaches.	Implement robust encryption, access controls.
Verify Implemented Change:	Enable Augmented	Scalability: Challenges in scaling	Performance degradation, increased	Invest in scalable infrastructure,

Table 10 Data Science Use Cases for the various process in Software Change & Configuration Management sub function. Source : Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Automated verification of change impact based on historical data.	Decision Making	verification algorithms.	processing time.	consider cloud solutions.
Release and Close Change: Data-driven release management for efficient closure based on historical patterns.	Create Dynamic Processes for Fast Execution	Alignment with business objectives: Misalignment with release goals.	Inefficient closure, potential errors.	Regularly align release objectives with business goals.

Management of product content and traceability benefits from automated traceability mechanisms, ensuring accurate tracking based on historical data. This contributes to the business agility goal of creating dynamic resources for fast execution by minimizing errors and improving overall traceability.

Documenting product branches and content is streamlined through data-driven documentation processes. Integration challenges are addressed through compatibility assessments and collaboration with IT teams, ensuring a smooth integration of documentation algorithms into existing systems.

Efficient management of product variants is achieved through machine learning, aligning with the goal of enabling augmented decision-making. Privacy and security concerns are addressed through robust encryption and access controls, safeguarding sensitive variant-related data.

Optimizing product builds with data-driven insights ensures a more efficient and responsive build process. Challenges related to scalability are mitigated through strategic investments in scalable infrastructure and consideration of cloud solutions.

Automated release management ensures efficient and accurate releases based on historical patterns. Implementing standardized release procedures addresses challenges related to the lack of standardization, minimizing errors, and ensuring a more streamlined release process.

Incorporating AI into Software Build & Release Management establishes a foundation for a more agile and responsive process, allowing organizations to adapt to changing requirements with enhanced efficiency and accuracy. Table 11 summarizes the different data science use cases in this domain, associated challenges and risk along with the proposed mitigation strategies that can be taken by organizations.

Table 11 Data Science Use Cases for the various process in Software Build & Release Management sub function. Source : Author

Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Define Product Content to Specification: Data-driven content definition based	Enable Augmented Decision Making	Lack of skilled workforce: Limited expertise in content definition.	Inaccurate content definition, potential errors.	Provide training programs, collaborate with experts.

Table 11 Data Science Use Cases for the various process in Software Build & Release Management sub function. Source : Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
on historical specifications.				
Manage Product Content and Traceability: Automated traceability mechanisms for accurate tracking based on historical data.	Enable Augmented Decision Making	Data quality and availability: Incomplete or unreliable traceability data.	Inaccurate tracking, potential issues.	Implement data quality checks, invest in data cleansing.
Document Product Branches and Content: Data-driven documentation for efficient and accurate documentation.	Enable Augmented Decision Making	Integration with existing systems: Difficulty in integrating documentation algorithms.	Workflow disruptions, inconsistent documentation.	Conduct system compatibility assessments, work with IT teams.
Manage Product Variants: Machine learning for	Enable Augmented Decision Making	Privacy and security concerns: Protecting	Unauthorized access, data breaches.	Implement robust encryption,

Table 11 Data Science Use Cases for the various process in Software Build & Release Management sub function. Source : Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
streamlined management of product variants.		sensitive variant data.		access controls.
Manage Product Builds: Data-driven insights for optimized build processes based on historical data.	Create Dynamic Processes for Fast Execution	Scalability: Challenges in scaling build optimization algorithms.	Performance degradation, increased processing time.	Invest in scalable infrastructure, consider cloud solutions.
Manage Product Releases: Automated release management for efficient and accurate releases based on historical patterns.	Create Dynamic Processes for Fast Execution	Lack of standardization: Inconsistencies in release processes.	Inefficient release processes, potential errors.	Implement standardized release procedures.

Software Test & Quality Management: The intersection of AI and Software Test & Quality Management ushers in a new era of precision and efficiency in testing processes. Table 12 summarizes the different data science use cases in this domain, associated challenges and risk along with the proposed mitigation strategies that can be taken by organizations. Planning test cases is expedited with data-driven insights based on historical test data, aligning with the business agility goals of creating dynamic resources for fast execution. Machine learning algorithms optimize the planning process, providing testers with insights into optimal test case scenarios.

Automated definition of test cases, guided by data science, further enhances the testing process. This aligns with the business agility goal of enabling augmented decision-making by providing automated recommendations for efficient and comprehensive test case scenarios.

The execution of test cases is transformed through data-driven testing, ensuring comprehensive coverage based on historical performance data. Integration challenges are addressed through compatibility assessments and collaboration with IT teams, ensuring a smooth integration of testing algorithms into existing systems.

Machine learning-driven management of test cases streamlines the overall testing process. Privacy and security concerns are addressed through robust encryption and access controls, safeguarding sensitive testing-related data.

Automated evaluation of test cases and quality, guided by data science, ensures a more accurate and efficient assessment of test effectiveness. This aligns with the business agility goal of improving behavioral awareness by providing real-time insights into the quality of software under test.

Review and approval of test cases are streamlined through automated processes guided by data science. Standardized review procedures address challenges related to the lack of standardization, minimizing errors, and ensuring a more efficient review process.

Incorporating AI into Software Test & Quality Management not only enhances the precision and coverage of testing processes but also establishes a foundation for more agile and responsive quality assurance.

Table 12 Data Science Use Cases for the various process in Software Test & Quality Management sub function. Source : Author

Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Plan Test Cases: Data-driven test planning based on historical test data.	Enable Augmented Decision Making, Create Dynamic Resources for Fast Execution	- Lack of skilled workforce: Limited expertise in test planning.	Inefficient test planning, potential issues.	Provide training programs, collaborate with experts.
Define Test Cases: Automated test case definition guided by data science.	Enable Augmented Decision Making	- Data quality and availability: Incomplete or unreliable test case data.	Inaccurate test case definition, potential issues.	Implement data quality checks, invest in data cleansing.
Execute Test Cases: Data-driven test execution for comprehensive testing based on historical performance data.	Create Dynamic Resources for Fast Execution	- Integration with existing systems: Difficulty in integrating testing algorithms.	Workflow disruptions, inconsistent test execution.	Conduct system compatibility assessments, work with IT teams.
Manage Test Cases: Machine learning for streamlined management of test cases based on historical data.	Enable Augmented Decision Making	- Privacy and security concerns: Protecting sensitive test case data.	Unauthorized access, data breaches.	Implement robust encryption, access controls.

Table 12 Data Science Use Cases for the various process in Software Test & Quality Management sub function. Source : Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Evaluate Test Cases: Automated evaluation guided by data science for accurate assessment of test case effectiveness.	Improve Behavioral Awareness	- Scalability: Challenges in scaling evaluation algorithms.	Performance degradation, increased processing time.	Invest in scalable infrastructure, consider cloud solutions.
Evaluate Test Results and Quality: Data-driven quality evaluation based on historical results and performance data.	Improve Behavioral Awareness	- Alignment with business objectives: Misalignment with quality goals.	Ineffective quality evaluation, potential risks.	Regularly align quality objectives with business goals.
Review and Approve Test Cases: Automated review mechanisms guided by data science.	Improve Behavioral Awareness	- Lack of standardization: Inconsistencies in test case review processes.	Inefficient review processes, potential errors.	Implement standardized review procedures.
Generate Reports and Manage Dashboards: Data-driven reporting and dashboard	Create Dynamic Resources for Fast Execution	- Privacy and security concerns: Protecting sensitive testing data.	Unauthorized access, data breaches.	Implement robust encryption, access controls.

Table 12 Data Science Use Cases for the various process in Software Test & Quality Management sub function. Source : Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
management for dynamic insights.				

Software Issues & Defect Management: The integration of AI into Software Issues & Defect Management revolutionizes the identification, prioritization, and resolution of issues, fostering a more efficient and responsive problem-solving ecosystem. Table 13 summarizes the different data science use cases in this domain, associated challenges and risk along with the proposed mitigation strategies that can be taken by organizations. Data-driven identification of issues enhances behavioral awareness, providing stakeholders with real-time insights into potential challenges.

Machine learning-driven prioritization of issues optimizes the overall issue management process. This aligns with the business agility goal of improving behavioral awareness by providing teams with insights into critical issues that require immediate attention.

Efficient evaluation of issue resolution is achieved through data-driven insights based on historical data. Integration challenges are addressed through compatibility assessments and collaboration with IT teams, ensuring a smooth integration of issue resolution algorithms into existing systems.

Automated determination of issue disposition, guided by data science, further streamlines the resolution process. Privacy and security concerns are addressed through robust encryption and access controls, safeguarding sensitive issue-related data.

Data-driven tracking of issues ensures real-time insights into issue resolution based on historical data. Challenges related to scalability are mitigated through strategic investments in scalable infrastructure and consideration of cloud solutions.

Automated reporting and dashboard management, guided by data science, enhance the overall visibility into the status of issues. Implementing standardized reporting procedures addresses challenges related to the lack of standardization, minimizing errors, and ensuring a more streamlined reporting process.

Table 13 Data Science Use Cases for the various process in Software Issues & Defect Management sub function. Source : Author

Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
- Identify and Document Issues: Data-driven issue identification for efficient problem-solving.	Improve Behavioral Awareness	- Lack of skilled workforce: Limited expertise in issue identification.	Inefficient issue identification, potential delays.	Provide training programs, collaborate with experts.
- Prioritize Issues: Machine learning for optimized issue prioritization based on historical data.	Improve Behavioral Awareness	- Data quality and availability: Incomplete or unreliable issue data.	Suboptimal prioritization, potential inefficiencies.	Implement data quality checks, invest in data cleansing.
- Evaluate Issues Resolution: Data-driven insights for efficient evaluation of issue resolution based on historical data.	Enable Augmented Decision Making	- Integration with existing systems: Difficulty in integrating issue resolution algorithms.	Workflow disruptions, inconsistent evaluations.	Conduct system compatibility assessments, work with IT teams.

Table 13 Data Science Use Cases for the various process in Software Issues & Defect Management sub function. Source : Author

Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
- Determine Issue Disposition: Automated disposition determination guided by data science.	Enable Augmented Decision Making	- Privacy and security concerns: Protecting sensitive issue data.	Unauthorized access, data breaches.	Implement robust encryption, access controls.
- Track Issues: Data-driven tracking for real-time insights into issue resolution based on historical data.	Enable Augmented Decision Making	- Scalability: Challenges in scaling issue tracking algorithms.	Performance degradation, increased processing time.	Invest in scalable infrastructure, consider cloud solutions.
- Generate Reports and Manage Dashboards: Data-driven reporting and dashboard management for dynamic insights.	Create Dynamic Resources for Fast Execution	- Lack of standardization: Inconsistencies in reporting processes.	Inefficient reporting, potential errors.	Implement standardized reporting procedures.

Incorporating AI into Software Issues & Defect Management establishes a foundation for a more agile and responsive problem-solving process, allowing organizations to address challenges with enhanced efficiency and accuracy.

4.1.7 Specialized Design

The integration of data science within the Specialized Design function of Product Design and Development organizations offers a transformative approach to various activities. In this context, data science methodologies are applied to optimize processes ranging from Artwork & Label Design to Emission & Energy Management Analysis. This section explores how data science can be applied to the below activities within this function.

- Artwork & Label Design
- Formulation Development
- Mechatronic Systems Concept Design
- ETO Design Automation
- Packaging Design
- Interior & Exterior Trim Design
- Drive Assistant System Development & Autonomous Driving
- Battery Cell Design
- Battery Module & Pack Design
- Driving Behavior & Safety Simulation
- NVH & Acoustics Analysis
- Emission & Energy Management Analysis
- Hybrid /Renewable Energy Management

4.1.7.1 Artwork & Label Design

The integration of data science into the realm of Artwork & Label Design, particularly within the Specialized Design function of Product Design and Development, holds substantial potential for enhancing efficiency and precision. This section explores how data science methodologies can be applied to activities as shown in *Figure 81*, such as designing label layout and artwork, managing product and pallet labeling, overseeing formula information, and reviewing and releasing artwork for production.

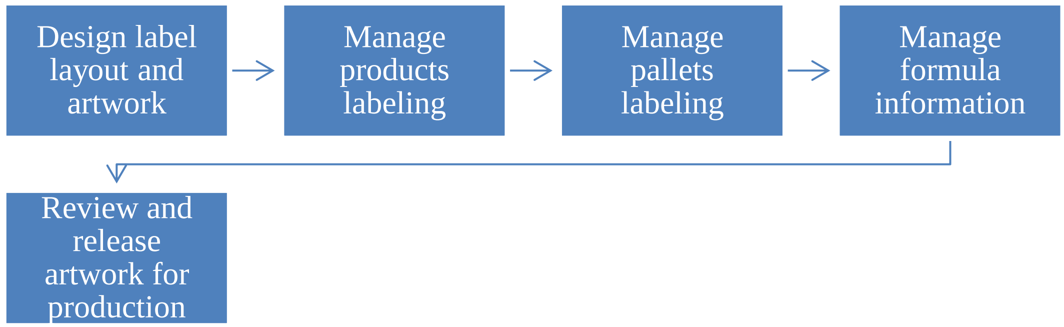

Figure 82 Typical Artwork & Label Design Process Flow. Source: Author

Designing label layout and artwork benefits from data science through automated design tools. Algorithms can analyze historical design data, user preferences, and industry trends, providing insights that inform the creation of visually appealing and compliant label layouts. Research has shown that data-driven design tools significantly contribute to design optimization and user satisfaction (Ferrero et al., 2020).

Managing product and pallet labeling is streamlined through data-driven systems. Machine learning models can automate the assignment of labels based on product specifications, ensuring accuracy and compliance with regulatory standards (Lee & Ahmed-Kristensen, 2023). This not only reduces manual efforts but also minimizes the risk of labeling errors.

Handling formula information is optimized by data science through automated data validation and verification processes. Algorithms can analyze formula data for consistency, flagging potential discrepancies and contributing to overall data quality assurance (Meierhofer et al., 2019).

Reviewing and releasing artwork for production benefits from data-driven quality control mechanisms. Artificial Intelligence (AI) algorithms can analyze artwork designs against predefined criteria, ensuring adherence to branding guidelines and regulatory requirements (Ribeiro et al., 2014). This automated review process contributes to faster and more reliable artwork approval.

In summary, the integration of data science into Artwork & Label Design activities within the Specialized Design function of Product Design and Development brings forth improvements in design optimization, labeling management, formula information handling, and artwork quality control. Leveraging data-driven insights enhances precision, reduces manual efforts, and contributes to the overall efficiency of the specialized design processes (Ferrero et al., 2020; Lee & Ahmed-Kristensen, 2023; Meierhofer et al., 2019; Ribeiro et al., 2014; Wang & Muzzolini, 2011).

4.1.7.2 Formulation Development

In the realm of Product Design and Development, specifically within the Specialized Design function, data science plays a crucial role in optimizing Formulation Development processes as shown in *Figure 83*. This section explores how data science can be effectively applied to activities such as developing formulas, managing formula alternatives, optimizing product formulations, managing new product formulation development, validating product formulations, managing trial batches, and facilitating the handover from development to commercialization.

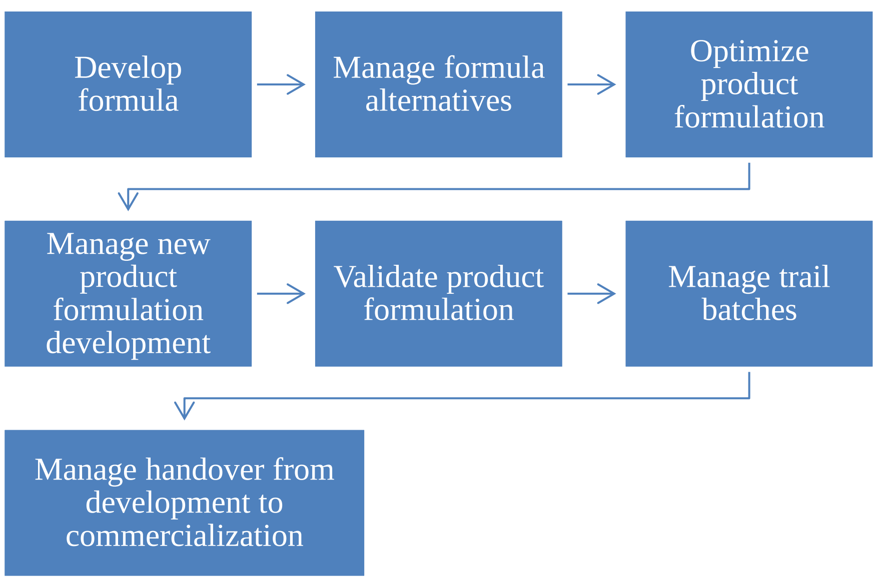

Figure 84 Typical Formulation Development Process Flow. Source: Author

Data Science in Formulation Development:

Developing formulas benefits from data science through predictive modeling and analysis of diverse data sources. Machine learning algorithms can analyze historical formulation data, ingredient properties, and market trends to suggest optimal formulas. These predictive models aid in reducing the time and resources required for formula development (Eberle et al., 2014).

Managing formula alternatives involves the application of decision-making algorithms. Data science enables the evaluation of alternative formulations based on various criteria such as cost, availability of ingredients, and compliance with regulatory standards. This ensures a systematic and informed approach to formula management (Fridgeirsdottir et al., 2016).

Optimizing product formulation leverages data science for advanced analytics. Machine learning algorithms can analyze complex relationships between multiple variables, allowing for the identification of the most efficient and effective formulations. This results in improved product quality and resource utilization (Zhang et al., 2017).

Managing new product formulation development benefits from predictive analytics. Data science can forecast potential challenges and requirements for new product formulations based on historical development data. This proactive approach supports efficient planning and resource allocation in the early stages of product development (Mehta et al., 2019).

Validating product formulations is streamlined through data-driven quality analysis. Machine learning models can assess the alignment of formulations with quality standards, identifying potential issues before the validation stage. This predictive validation enhances the overall robustness and reliability of the product development process.

Managing trial batches is facilitated by data science through process optimization. Predictive modeling can analyze trial batch data, optimizing production processes and identifying potential areas for improvement. This iterative approach ensures continuous enhancement of formulation development processes.

The handover from development to commercialization benefits from data science-driven insights. Predictive analytics can assess the readiness of formulations for commercial-scale production, reducing the risks associated with scaling up production and ensuring a smoother transition.

In summary, the integration of data science into Formulation Development processes within the Specialized Design function significantly enhances efficiency, decision-making, and overall product quality. From predictive modeling in formula development to data-driven validation and optimization, data science contributes to a more systematic, informed, and streamlined approach to product design and development. These advancements align with contemporary research findings and underscore the transformative impact of data science in the formulation development domain (Eberle et al., 2014; Fridgeirsdottir et al., 2016; Mehta et al., 2019; Snehal et al., 2023; L. Zhang et al., 2017).

4.1.7.3 Mechatronic Systems Concept Design

In the realm of Product Design and Development, the application of data science in Mechatronic Systems Concept Design offers opportunities to enhance the efficiency and effectiveness of various activities as shown in *Figure 85*. This section delves into the utilization of data science in developing mechatronic components, creating mechatronic concepts, developing mechatronics systems, simulating, and validating mechatronic systems, and reviewing and releasing these systems.

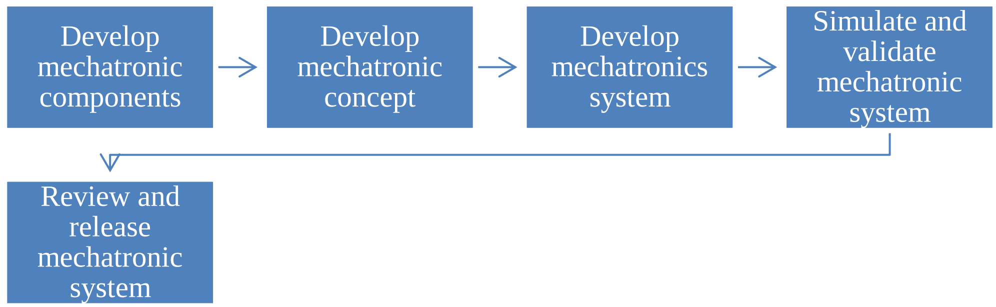

Figure 86 Typical Mechatronic Systems Concept Design Process Flow.   Source: Author

Developing Mechatronic Components: Data science contributes to the development of mechatronic components by analyzing historical design data and utilizing predictive modeling. Algorithms, as discussed by Couturier et al. (2014), can identify patterns in component designs, recommend optimal materials, and predict performance characteristics, streamlining the component development process.

Developing Mechatronic Concept: Utilizing historical concept data, data science aids in developing mechatronic concepts by suggesting innovative ideas and configurations. The application of machine learning algorithms, as highlighted by Chami & Bruel (2015), supports the identification of novel concepts aligned with project requirements, fostering creativity in the design process.

Developing Mechatronics System: Data science plays a pivotal role in the development of mechatronics systems by integrating various components seamlessly. Xu et al. (2006) discuss the application of optimization algorithms that consider factors such as compatibility, efficiency, and cost-effectiveness, aiding in the creation of well-integrated mechatronic systems.

Simulating and Validating Mechatronic System: Simulation and validation processes are optimized through data-driven approaches. Miatliuk et al. (2010) emphasize the use of data science to develop realistic simulation models, which, when combined with historical performance data, enable accurate validation of mechatronic systems. This ensures reliability before physical prototypes are built.

Review and Release Mechatronic System: Data science contributes to the review and release of mechatronic systems by automating the analysis of system performance data. Zheng et al. (2014) discuss the application of data analytics in evaluating simulation results, identifying potential issues, and supporting an informed decision-making process during the review and release phases.

In summary, the infusion of data science into Mechatronic Systems Concept Design within the Product Design and Development framework brings forth improvements in component development, concept ideation, system integration, simulation, validation, and the review and release processes. The data-centric approach enhances creativity, efficiency, and decision-making, ultimately contributing to the development of robust and innovative mechatronic systems (Chami & Bruel, 2015; Couturier et al., 2014; Miatliuk et al., 2010; Xu et al., 2006; Zheng et al., 2014).

4.1.7.4 ETO Design Automation

In the realm of Product Design and Development, the integration of data science into Engineer-to-Order (ETO) Design Automation processes presents opportunities for improved efficiency and innovation. This section explores the application of data science in activities as shown in *Figure 87*, such as defining parametric automation models, maintaining, and updating design model parameters, managing customer order input, generating designs, and reviewing generated designs.

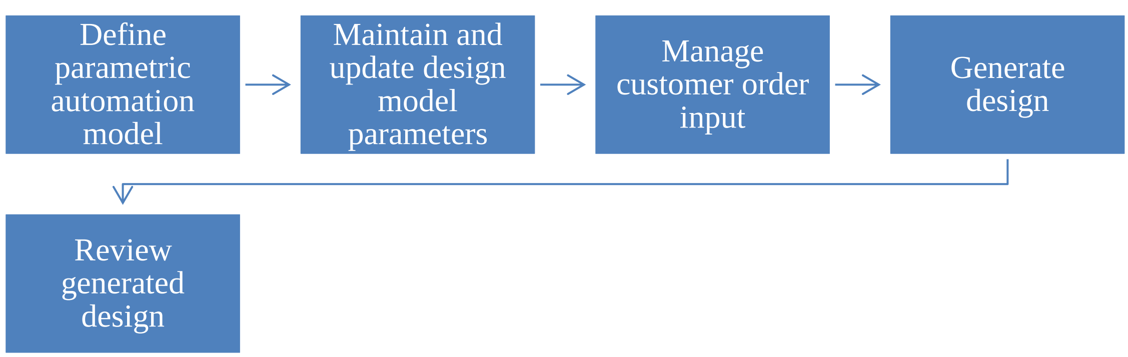

Figure 88 Engineer To Order Design Automation Process Flow. Source: Author

Define Parametric Automation Model: Data science contributes to the definition of parametric automation models by leveraging machine learning algorithms. These algorithms can analyze historical design data, considering various parameters and constraints, to create models that adapt to specific engineering needs. The utilization of machine learning models for parametric design is well-documented in literature (Altarturi et al., 2017).

Maintain and Update Design Model Parameters: Continuous maintenance and updates to design model parameters are streamlined through data science. Predictive analytics models can analyze trends in design changes over time, helping anticipate parameter updates. This ensures that design models remain current and aligned with evolving engineering requirements (Bakar et al., 2017).

Manage Customer Order Input: Data science aids in managing customer order input by utilizing Natural Language Processing (NLP) techniques. NLP algorithms can process customer input, extract relevant information, and map it to design parameters. This not only enhances accuracy but also accelerates the translation of customer requirements into actionable design inputs (Esteca et al., 2012).

Generate Design: The generation of designs benefits from data science through algorithmic design optimization. Machine learning algorithms can analyze vast design possibilities, considering various parameters and historical design successes, to generate optimized designs. This approach aligns with research highlighting the role of machine learning in design optimization (Maalej et al., 2016).

Review Generated Design: Data science facilitates the review of generated designs by automating the analysis of design outputs. Automated evaluation tools powered by machine learning models can assess design quality, adherence to specifications, and potential areas for improvement. This data-driven review process ensures a more thorough and efficient design assessment (Palomares, 2014).

In summary, the integration of data science into Engineer-to-Order (ETO) Design Automation processes within the Product Design and Development domain enhances various facets of the design lifecycle. From defining parametric models to reviewing generated designs, data science contributes to efficiency, innovation, and accuracy in ETO design automation (Altarturi et al., 2017; Bakar et al., 2017; Esteca et al., 2012; Maalej et al., 2016; Palomares, 2014).

4.1.7.5 Packaging Design

Within the realm of Product Design and Development, the Packaging Design function plays a crucial role in determining the physical presentation and protection of products. Integrating data science into this process can enhance efficiency, optimize designs, and improve decision-making. This section explores the application of data science in activities as shown in *Figure 89*, related to artwork development, pack specification definition, pack homologation, simulation and digital prototyping, and packaging concept design.

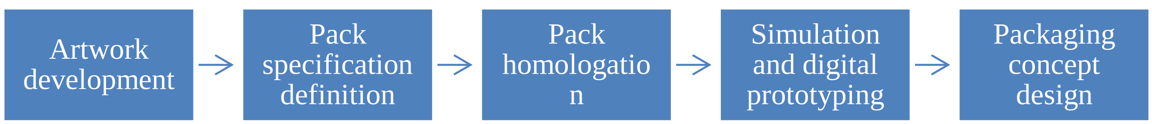

Figure 90 Typical Packaging Design Process Flow. Source: Author

Artwork Development: Data science contributes to artwork development by analyzing consumer preferences and market trends. Machine learning models can process historical artwork data and consumer feedback, providing insights to inform the design process. This ensures that packaging aligns with market expectations and enhances brand appeal (Bodyan et al., 2017).

Pack Specification Definition: Data science aids in defining pack specifications by leveraging predictive modeling. Algorithms can analyze historical data on material properties, cost factors, and environmental considerations to recommend optimal pack specifications. This data-driven approach ensures that specifications align with both functional and sustainable criteria (Feng et al., 2020).

Pack Homologation: Automated homologation processes benefit from data science-driven analysis. Predictive analytics models can assess regulatory requirements, industry standards, and historical compliance data to streamline homologation efforts. This ensures that packaging designs comply with relevant regulations, reducing time-to-market (Gan et al., 2022).

Simulation and Digital Prototyping: Data science enhances simulation and digital prototyping by utilizing machine learning algorithms for performance prediction. These models analyze material behavior, environmental conditions, and design parameters, enabling accurate simulations. This data-centric approach improves the efficiency of prototyping and minimizes the need for physical iterations.

Packaging Concept Design: Data science contributes to packaging concept design through generative algorithms. These algorithms explore various design possibilities based on historical design data, market trends, and consumer preferences. This iterative and data-driven process helps generate innovative and effective packaging concepts.

In summary, the integration of data science into the Packaging Design function within Product Design and Development optimizes various aspects of the packaging lifecycle. From artwork development informed by consumer insights to pack specification definition guided by predictive modeling, data science ensures efficient and sustainable packaging designs. Automated homologation processes and data-driven simulations further contribute to regulatory compliance and prototyping accuracy. Embracing data science in packaging design enhances the overall product development process, fostering innovation and sustainability (Bodyan et al., 2017; Feng et al., 2020; Gan et al., 2022).

4.1.7.6 Interior & Exterior Trim Design

Within the realm of Product Design and Development, the Interior & Exterior Trim Design function plays a pivotal role in shaping the aesthetics and functionality of automotive components. This section explores how data science can be applied to various activities as shown in *Figure 91***,** within this function, including the development of interior and exterior design assemblies, seating components, surrounding trim design, integration into the product, collaboration with OEMs and suppliers, and the validation and release of design results.

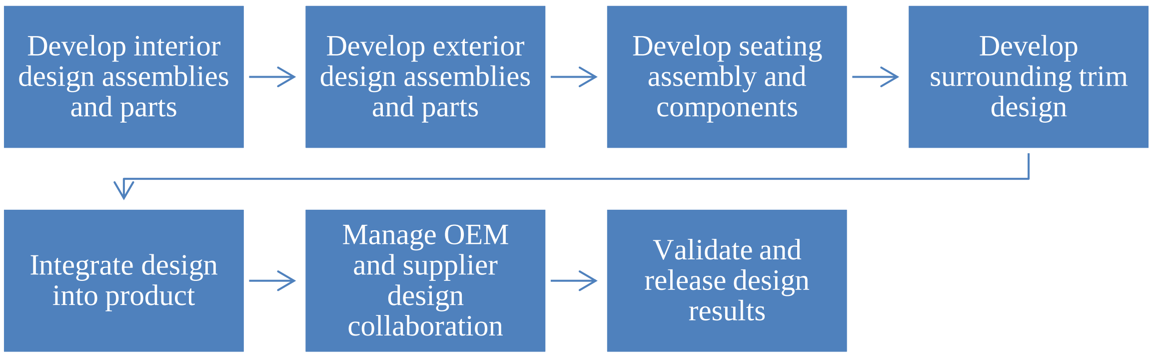

Figure 92 Typical Interior & Exterior Trim Design Process Flow. Source: Author

Data Science in Interior & Exterior Trim Design:

In the development of interior and exterior design assemblies and parts, data science can leverage predictive modeling to analyze historical design data and market trends. This facilitates the identification of design elements that align with consumer preferences and automotive industry standards (Feng et al., 2020).

For the development of seating assembly and components, data science plays a role in ergonomic analysis. Utilizing machine learning models, designers can optimize seating configurations based on user comfort, ensuring that the design aligns with both functional and aesthetic considerations (Ferrero et al., 2020).

Surrounding trim design benefits from data-driven pattern recognition and analysis. Natural Language Processing (NLP) algorithms can process design specifications, extract relevant information, and recommend design elements that enhance the overall aesthetic coherence of the trim (Volpentesta et al., 2004).

Integrating design into the product involves collaborative efforts with Original Equipment Manufacturers (OEMs) and suppliers. Data science supports this collaboration by analyzing real-time data on component availability, cost structures, and manufacturing capabilities, streamlining the integration process.

Managing OEM and supplier design collaboration is further optimized through data-driven project management. Predictive analytics models can identify potential bottlenecks, allowing for proactive issue resolution and ensuring seamless collaboration throughout the design phase.

Validation and release of design results are improved through data science by automating quality assurance processes. Machine learning models can analyze design specifications against industry standards, predicting potential issues and validating designs before release (Feng et al., 2020).

In conclusion, the integration of data science into Interior & Exterior Trim Design activities enhances various facets of the design process, from predicting consumer preferences and optimizing seating configurations to improving collaboration with OEMs and suppliers. This data-centric approach fosters more efficient, informed, and quality-driven design practices within the framework of Product Design and Development (Feng et al., 2020; Ferrero et al., 2020; Volpentesta et al., 2004).

4.1.7.7 Drive Assistant System Development & Autonomous Driving

In the context of Product Design and Development, specifically within the domain of Drive Assistant System Development & Autonomous Driving, the integration of data science plays a crucial role in advancing various activities as shown in *Figure 93*. This section explores how data science methodologies, drawing insights from notable research, can be applied to drive assistant system design studies, sensor setup definition and configuration, system and algorithm development, simulation and optimization, vehicle certification, and the validation and release of design results.

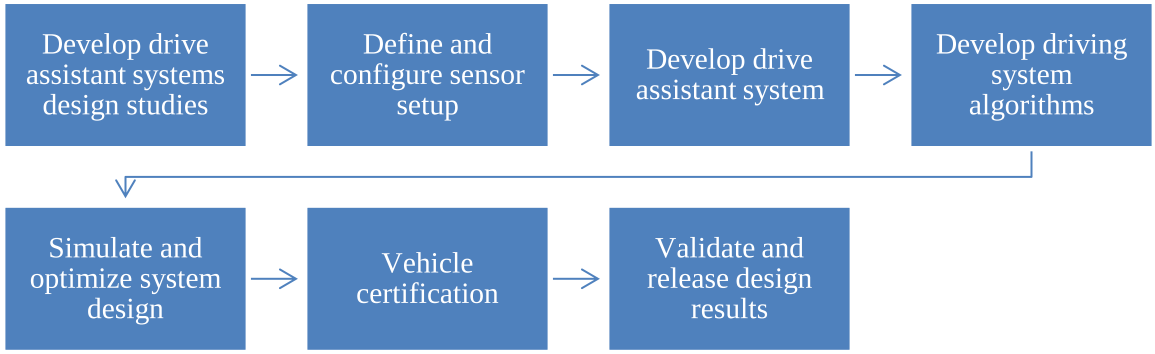

Figure 94 Drive Assistant System Development & Autonomous Driving Process Flow. Source: Author

Data science contributes to drive assistant system design studies by analyzing extensive datasets. Insights from Duy et al. (2019) emphasize the use of data analytics to understand user behavior, road conditions, and potential risks. This analysis guides the design studies to create systems that align with user needs and safety requirements.

In defining and configuring sensor setups, data science leverages advanced sensor technologies. Research by Hofmann et al. (2017) underscores the significance of sensor data fusion and machine learning algorithms for optimal configuration. Data science models enhance the accuracy and efficiency of sensor setups, crucial for reliable autonomous driving systems.

The development of drive assistant systems involves data-driven approaches to algorithm development. Liu et al. (2018) emphasize the use of machine learning for algorithm refinement. Data science techniques contribute to the creation of sophisticated algorithms that enhance system capabilities and responsiveness.

Simulating and optimizing system design benefits from data-driven simulations. Orlovska et al. (2020) stress the importance of virtual testing and optimization. Data science-driven simulations allow for the testing of various scenarios, improving system robustness and performance in diverse conditions.

Vehicle certification involves data-driven compliance assessments. Rigoll et al. (2022) highlight the role of data analytics in certifying systems' adherence to safety and regulatory standards. Data science facilitates comprehensive evaluation, ensuring that autonomous driving systems meet certification requirements.

Validation and release of design results are enhanced by data-driven validation processes. Zhang et al. (2023) emphasize real-world and simulated validation with machine learning-based anomaly detection. Data science models contribute to the validation process, identifying potential issues and ensuring the release of robust design results.

In summary, the integration of data science into Drive Assistant System Development & Autonomous Driving within the Product Design and Development domain is pivotal for advancing various activities. By leveraging insights from research studies, data science enhances system design studies, sensor setup definition, algorithm development, simulation, certification, and validation processes. This data-centric approach ensures the development of reliable and efficient autonomous driving systems in alignment with safety and regulatory standards (Duy et al., 2019; Hofmann et al., 2017; Liu et al., 2018; Orlovska et al., 2020; Rigoll et al., 2022; Zhang et al., 2023).

4.1.7.8 Battery Cell Design

In the domain of Product Design and Development, specifically focusing on the Battery Cell Design function, the integration of data science offers opportunities to enhance efficiency, optimize designs, and ensure the quality of battery cells. This section explores how data science can be applied to various activities as shown in *Figure 95***,** within the Battery Cell Design process, referencing relevant research.

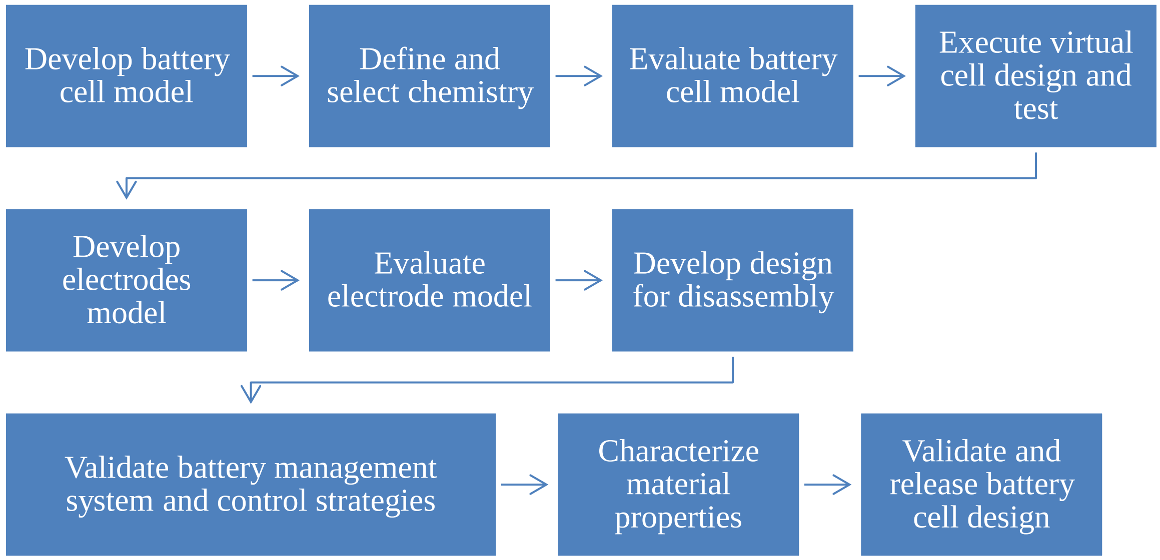

Figure 96 Typical Battery Cell Design Process Flow. Source: Author

Developing the battery cell model benefits data science through the utilization of predictive modeling. Machine learning models can analyze historical battery performance data and material properties, allowing for the creation of accurate and comprehensive battery cell models. This data-driven approach enhances the understanding of cell behavior and aids in the initial stages of design.

Defining and selecting chemistry involves data science by employing algorithms that assess chemical properties, performance characteristics, and safety considerations. This data-driven decision-making process ensures the optimal selection of battery chemistry based on historical data and known performance indicators.

Evaluating the battery cell model is enhanced by data science using simulation and modeling techniques. Finegan et al. (2021) highlight the application of advanced modeling to simulate cell behavior under various conditions, providing insights into performance metrics and potential issues.

Executing virtual cell design and testing benefits from data science by leveraging simulation tools and machine learning algorithms. These tools can predict the impact of design modifications on performance, allowing for virtual testing and optimization before physical prototypes are built (Thiede et al., 2019).

Developing electrodes models incorporates data science by utilizing algorithms that analyze material properties and performance data. Schnell et al. (2019) discuss the application of machine learning in electrode design, allowing for the creation of models that optimize performance and longevity.

Evaluating the electrode model is supported by data science through advanced analytics. Machine learning can identify patterns and correlations within electrode performance data, providing insights into areas for improvement and guiding iterative design processes.

Designing for disassembly involves data science in the analysis of material properties and connections within the battery cell. Dawson-Elli et al. (2018) discusses the importance of sustainable design practices, and data-driven approaches can aid in creating battery cells that are environmentally friendly and easy to disassemble.

Validating the battery management system and control strategies employs data science by using simulations and algorithms to assess the performance of control systems. Kauwe et al. (2019) emphasizes the role of modeling and simulation in optimizing battery management strategies for improved efficiency and safety.

Characterizing material properties benefits from data science through advanced analytics and machine learning. Ghadbeigi et al. (2015) highlight the application of data-driven methods in material characterization, allowing for more accurate assessments of material behavior under different conditions.

Validating and releasing the battery cell design incorporates data science through comprehensive analysis and simulation. By leveraging historical data and predictive modeling, organizations can ensure that the final design meets performance, safety, and environmental standards.

In summary, the integration of data science into Battery Cell Design activities within the Product Design and Development organization offers a data-driven approach to model development, chemistry selection, virtual testing, material characterization, and system validation. Leveraging predictive modeling, machine learning, and advanced analytics, organizations can optimize designs, enhance performance, and ensure the reliability and sustainability of battery cells, aligning with the evolving landscape of research in battery technology (Dawson-Elli et al., 2018; Finegan et al., 2021; Ghadbeigi et al., 2015; Kauwe et al., 2019; Schnell et al., 2019; Thiede et al., 2019).

4.1.7.9 Battery Module & Pack Design

The Battery Module & Pack Design function within an organization plays a crucial role in the development of efficient and reliable battery systems for various applications. Leveraging data science in this domain enhances the design process and ensures optimal performance and safety. This section explores the integration of data science into activities as shown in *Figure 97***,** such as developing battery module and pack models, designing cooling systems, performing thermal and vibration analyses, creating designs for disassembly, and validating and releasing battery module/pack designs.

The development of battery module models benefits from data science through the utilization of computational modeling techniques (Agarwal et al., 2010). Machine learning algorithms can analyze historical data on battery performance, aiding in the creation of accurate and predictive module models.

Evaluation of battery module models is enhanced by data science through automated analysis tools. Predictive analytics models can assess the performance and efficiency of module designs based on historical data, enabling quick and informed decision-making (Biosca, 2016).

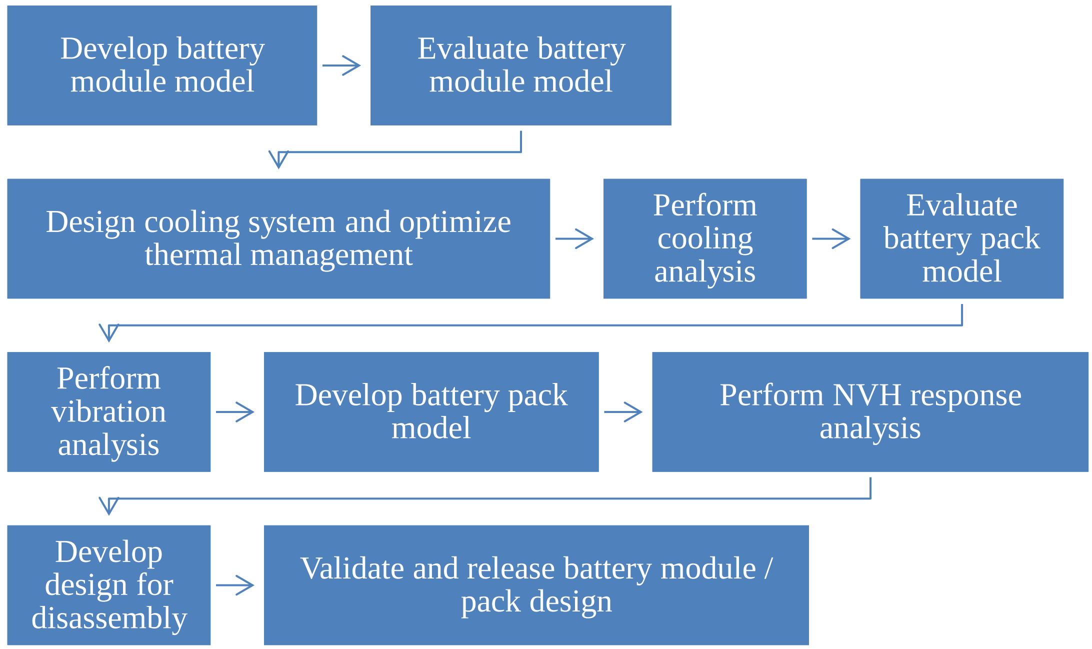

Figure 98 Typical Battery Module & Pack Design Process Flow. Source: Author

Designing cooling systems and optimizing thermal management are areas where data science plays a crucial role. Computational fluid dynamics (CFD) simulations, powered by data science, allow for the efficient design and optimization of cooling systems (Dawson-Elli et al., 2018). This ensures that battery modules and packs operate within safe temperature ranges, maximizing efficiency and lifespan.

Performing cooling analysis benefits from data science-driven simulations. Machine learning models can optimize cooling strategies based on real-time operating conditions, ensuring dynamic and adaptive thermal management (Finegan et al., 2021).

Evaluation of battery pack models incorporates data science through advanced analytical techniques. Machine learning algorithms can analyze structural and performance data to assess the integrity and efficiency of battery pack designs (Ghosh et al., 2021).

Performing vibration analysis is enhanced by data science through the application of finite element analysis (FEA) and machine learning algorithms. These tools can predict and analyze the impact of vibrations on battery components, informing design improvements.

Developing battery pack models benefits from data science by leveraging historical design data. Machine learning models can recommend optimal pack configurations based on past performance data, facilitating the creation of efficient and reliable designs.

Performing NVH (Noise, Vibration, and Harshness) response analysis is improved by data science through predictive modeling. Machine learning algorithms can analyze historical NVH data, helping to predict and address potential noise and vibration issues in battery packs.

Developing designs for disassembly incorporates data science by assessing the recyclability and sustainability of materials (Ghosh et al., 2021). Machine learning models can optimize design choices to facilitate the disassembly and recycling process.

Validation and release of battery module/pack designs benefit from data science by ensuring compliance with safety and performance standards. Predictive analytics models can assess design attributes, supporting the validation process and contributing to the release of optimized designs.

In summary, the integration of data science into Battery Module & Pack Design activities enhances the entire design lifecycle. From the development and evaluation of module and pack models to the optimization of cooling systems, vibration and NVH analyses, and the creation of disassembly-friendly designs, data science ensures efficient, safe, and sustainable battery designs. Leveraging historical data and advanced analytical tools, organizations can drive innovation and reliability in the development of battery modules and packs (Agarwal et al., 2010; Biosca, 2016; Dawson-Elli et al., 2018; Finegan et al., 2021; Ghosh et al., 2021).

4.1.7.10 Driving Behavior & Safety Simulation

Within the organizational context of "Driving Behavior & Safety Simulation," the integration of data science offers substantial opportunities to enhance the efficiency and accuracy of various activities as shown in *Figure 99*. This section explores the application of data science in the preparation of simulation setups, vehicle dynamic behavior simulation, driving safety simulation, design and simulation of safety components, and the analysis and review of simulation results.

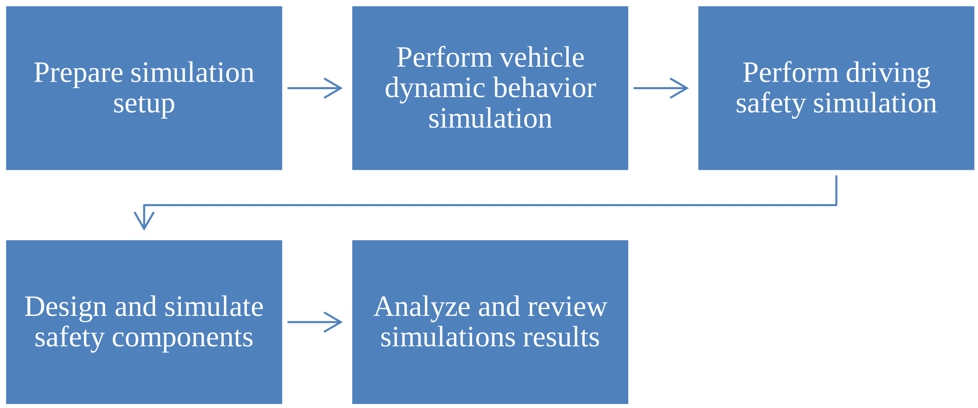

Figure 100 Typical Driving Behavior & Safety Simulation Process Flow. Source: Author

The preparation of simulation setups benefits from data science through predictive modeling. Machine learning algorithms can analyze historical simulation data and contextual factors, predicting optimal setups for various scenarios. This enhances the efficiency of the simulation preparation process.

Performing vehicle dynamic behavior simulation leverages data science to enhance accuracy. Advanced modeling techniques, as discussed by Fan et al. (2018), allow for more precise representations of vehicle dynamics. Machine learning models can continuously learn from real-world data, improving the fidelity of dynamic behavior simulations.

Driving safety simulation is enhanced by data science through the incorporation of predictive analytics. Algorithms, as highlighted by Bouhoute et al. (2019), can assess potential safety risks based on historical simulation results and real-world driving data. This enables proactive identification of safety concerns and the development of effective safety strategies.

The design and simulation of safety components are optimized through data-driven approaches. Machine learning algorithms can analyze safety component designs and predict their performance under various conditions. This enables the iterative refinement of safety components, aligning them with both safety standards and real-world driving scenarios.

Analyzing and reviewing simulation results benefit from data science-driven analytics. Rudin-Brown et al. (2011) emphasize the importance of objective analysis in driving simulation studies. Data science enables the automated processing of simulation results, identifying patterns, outliers, and areas for improvement more efficiently than traditional methods.

In summary, the integration of data science methodologies in the Driving Behavior & Safety Simulation function contributes to the optimization of simulation setups, accuracy in vehicle dynamic behavior simulations, proactive identification of safety concerns, iterative refinement of safety components, and efficient analysis of simulation results. Drawing insights from the cited works, this data-centric approach ensures a more advanced and informed simulation process within the organizational context (Andria et al., 2016; Bouhoute et al., 2019; Fan et al., 2018; Rudin-Brown et al., 2011).

4.1.7.11 NVH & Acoustics Analysis

In the specialized domain of NVH (Noise, Vibration, and Harshness) & Acoustics Analysis within the dedicated organization, the application of data science becomes pivotal in achieving optimal performance and efficiency. This section explores how data science can be effectively employed across various activities as shown in *Figure 101*, including driveline integration NVH and acoustics analysis, optimization for electrification, electrical motor noise, shift feeling, transmission NVH and acoustics, timing belt optimization, intake-exhaust acoustics analysis and optimization, hybrid powertrain NVH analysis, engine start-stop optimization, time domain transfer path analysis, ICE (Internal

Combustion Engine) efficiency optimization for NVH and acoustics, low-frequency driveline noise, vibration, and drivability optimization, and powertrain noise optimization.

Analyzing driveline integration NVH and acoustics involves processing vast datasets related to driveline components and their integration. Data science methodologies, such as machine learning algorithms, can be employed to analyze these datasets, extracting patterns, and identifying potential NVH and acoustics issues. The work of Azadi et al. (2009) showcases the application of data science in addressing NVH challenges in automotive systems.

Optimizing NVH and acoustics for electrification requires a comprehensive understanding of the unique acoustic characteristics of electric powertrains. Data science facilitates the analysis of these characteristics and supports the optimization process. Holehouse et al. (2019) emphasize the significance of leveraging data science in optimizing NVH for electric vehicles.

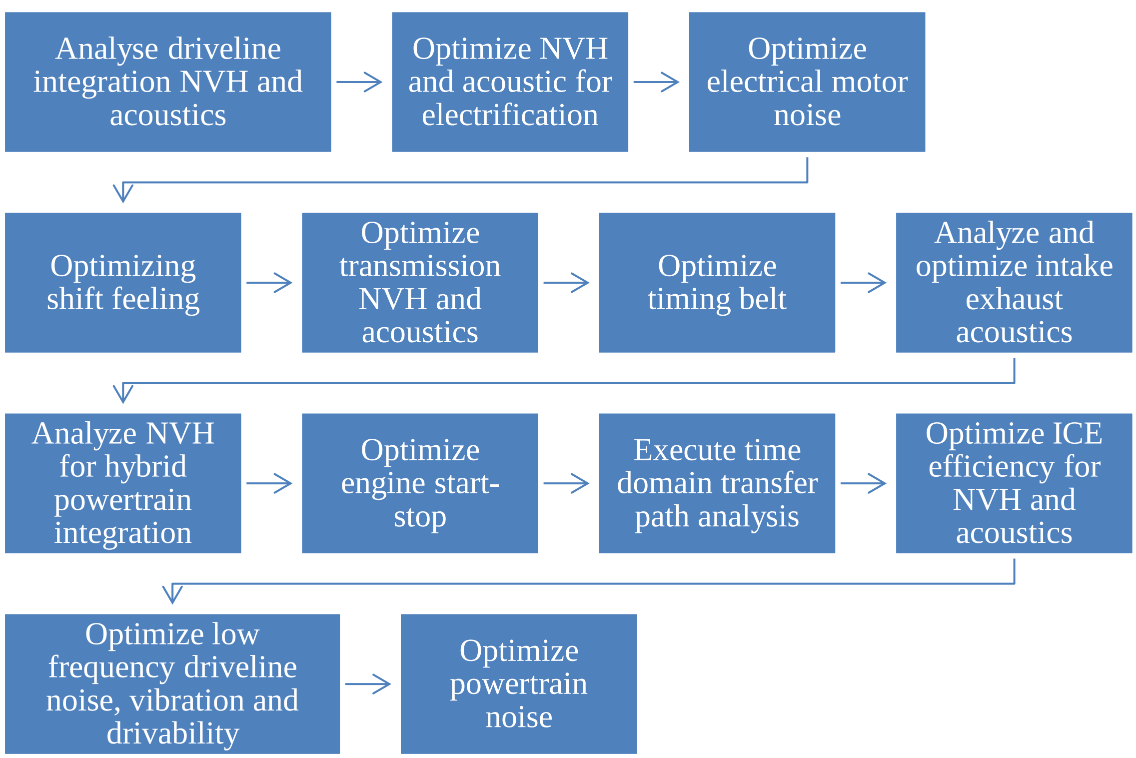

Figure 102 Typical NVH & Acoustics Analysis Process Flow. Source: Author

Optimizing electrical motor noise involves data-driven approaches to identify noise sources and patterns. Data science models, as demonstrated by Kumar et al. (2017), can aid in optimizing electric motor noise characteristics, ensuring a quieter and more refined driving experience.

The optimization of shift feeling involves analyzing data related to transmission shifts and driver inputs. Machine learning algorithms can process this data to identify patterns and optimize shift strategies, contributing to a smoother driving experience (Song et al., 2022).

Optimizing transmission NVH and acoustics involves a comprehensive analysis of transmission components and their interactions. Data science techniques, as highlighted by Souksavanh & Liu (2020), can uncover insights for optimizing the NVH and acoustics characteristics of transmissions.

Optimizing timing belts requires analyzing vibration and noise characteristics during engine operation. Data science can assist in identifying optimal timing belt configurations to minimize noise and vibration (Taratorkin et al., 2020).

Analyzing and optimizing intake-exhaust acoustics involves processing extensive datasets related to airflow and combustion. Data science, as demonstrated by Taratorkin et al. (2020), aids in understanding and optimizing acoustics in the intake and exhaust systems.

Analyzing NVH for hybrid powertrain integration involves integrating data from multiple power sources. Data science models can analyze the complex interactions between electric and internal combustion components to address NVH challenges effectively.

Optimizing engine start-stop functionality requires analyzing data related to engine restarts and shutdowns. Data science can identify optimal strategies for minimizing NVH during start-stop events.

Executing time domain transfer path analysis involves processing time-domain vibration data to identify and prioritize noise paths. Data science can automate this analysis, improving efficiency and accuracy in identifying key contributors to NVH issues.

Optimizing ICE efficiency for NVH and acoustics involves analyzing engine operation data to improve efficiency without compromising noise and vibration characteristics.

Optimizing low-frequency driveline noise, vibration, and drivability involves leveraging data science models to understand and address low-frequency NVH issues, ensuring a comfortable driving experience.

Optimizing powertrain noise involves analyzing data related to powertrain components and their interactions. Data science can aid in identifying and mitigating noise sources to achieve a refined and harmonious powertrain sound.

In summary, the integration of data science into the NVH & Acoustics Analysis function proves instrumental in addressing a myriad of challenges associated with noise, vibration, and harshness in automotive systems. Leveraging machine learning algorithms and advanced analytics, organizations can optimize various aspects of powertrain and driveline components, ensuring a harmonious and efficient driving experience (Azadi et al., 2009; Holehouse et al., 2019; Kumar et al., 2017; Song et al., 2022; Souksavanh & Liu, 2020; Taratorkin et al., 2020).

4.1.7.12 Emission & Energy Management Analysis

Within the organization focused on "Emission & Energy Management Analysis," data science can significantly contribute to various critical activities aimed at optimizing vehicle performance, reducing emissions, and enhancing energy efficiency. This section explores the application of data science in key functions as shown in *Figure 103***,** such as intake, exhaust, and engine actuation optimization; after-treatment efficiency optimization; transmission powertrain integration analysis; thermal management efficiency optimization; vehicle energy management target setting; in-cylinder engine performance optimization; lubrication circuit development; electrified powertrain efficiency optimization; engine thermal system development analysis and optimization; and air path system modeling.

Data science supports intake, exhaust, and engine actuation optimization by analyzing historical engine performance data. Machine learning models can identify patterns and correlations, enabling the optimization of intake and exhaust processes, engine actuation strategies, and combustion parameters (He et al., 2020; İlker et al., 2013).

After-treatment efficiency optimization benefits from data-driven analysis. Predictive analytics models can assess the effectiveness of after-treatment systems, recommending adjustments to optimize emission reduction while considering real-time operational conditions (Mohammad et al., 2023).

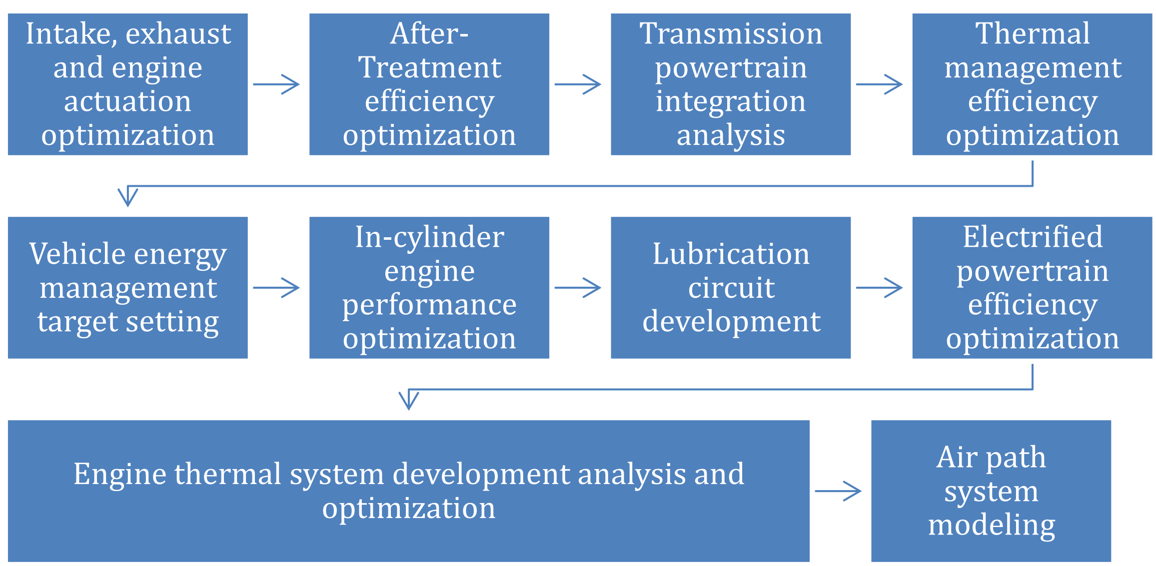

Figure 104 Emission & Energy Management Analysis Process Flow. Source: Author

Transmission powertrain integration analysis leverages data science to optimize powertrain configurations. Machine learning algorithms analyze performance data to recommend transmission configurations that balance efficiency, performance, and emissions (Loro & Lacaille, 2017).

Thermal management efficiency optimization is enhanced by data science-driven models. Predictive analytics can optimize thermal management systems by analyzing historical data, weather conditions, and engine parameters to improve overall efficiency (Pinto et al., 2020).

Vehicle energy management target setting involves data science in defining optimal energy usage targets. Machine learning algorithms analyze vehicle dynamics, driver behavior, and environmental conditions to set targets that balance performance and energy efficiency.

In-cylinder engine performance optimization employs data science to enhance combustion efficiency. Machine learning models analyze in-cylinder conditions and historical performance data to optimize combustion strategies for improved efficiency and reduced emissions.

Lubrication circuit development benefits from data-driven analysis. Predictive models assess lubrication system performance, recommending circuit configurations that minimize energy consumption and enhance overall efficiency.

Electrified powertrain efficiency optimization leverages data science to enhance the efficiency of electrified propulsion systems. Machine learning algorithms analyze performance data to optimize power distribution, energy regeneration, and overall electrified powertrain efficiency.

Engine thermal system development analysis and optimization are facilitated by data science-driven models. Predictive analytics can analyze thermal system performance data to optimize cooling strategies, ensuring efficient heat dissipation, and minimizing energy consumption.

Air path system modeling involves data science in developing accurate and predictive models of the air intake and exhaust systems. Machine learning algorithms can analyze system dynamics, recommending optimizations for improved efficiency and reduced emissions.

In summary, the integration of data science into the "Emission & Energy Management Analysis" function enables optimization across various facets of vehicle performance. Leveraging historical data and predictive modeling, data science contributes to efficiency improvements, emission reduction, and overall enhancement of energy management strategies within the organization (He et al., 2020; İlker et al., 2013; Loro & Lacaille, 2017; Mohammad et al., 2023; Pinto et al., 2020).

4.1.7.13 Hybrid /Renewable Energy Management

Within the organizational domain of Hybrid/Renewable Energy Management, the incorporation of data science offers an innovative approach to enhance various activities as shown in *Figure 105*, ranging from test and simulation setup to competitor benchmarking.

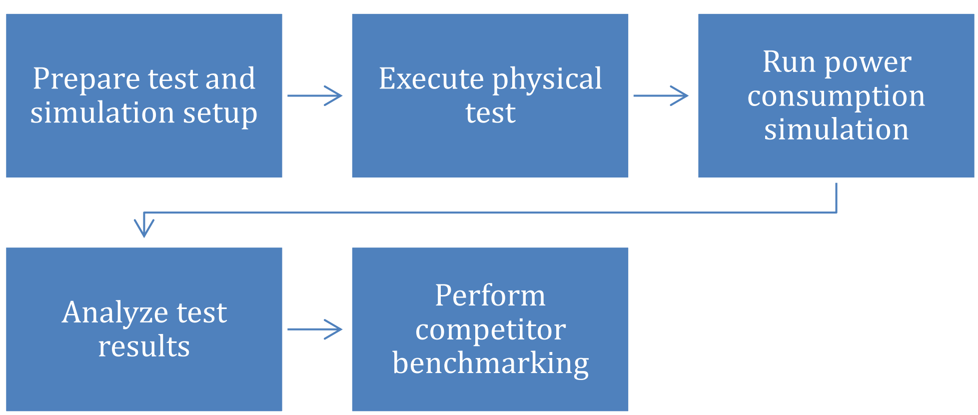

Figure 106 Hybrid /Renewable Energy Management Process Flow. Source: Author

This section explores how data science methodologies can be applied in the context of Hybrid/Renewable Energy Management, drawing insights from scholarly works.

The preparation of test and simulation setups benefits from data science by employing predictive modeling. Machine learning algorithms can analyze historical test data and contextual information to suggest optimal test configurations, enhancing the relevance and effectiveness of test setups (Guelleh et al., 2020).

Execution of physical tests is facilitated by data-driven automation. Internet of Things (IoT) devices and sensors, combined with machine learning algorithms, enable real-time data collection and analysis during physical tests. This ensures accurate and timely results, contributing to a more efficient testing process (Zell et al., 2008).

Running power consumption simulations are optimized through data science methodologies. Simulation models powered by machine learning algorithms can predict power consumption patterns, allowing for more accurate simulations and better understanding of energy management requirements (Ozkan et al., 2020).

Analyzing test results benefits from advanced analytics and statistical modeling. Data science techniques, including regression analysis and pattern recognition, can uncover valuable insights from complex test datasets, providing a comprehensive understanding of energy system performance (Giaouris et al., 2013; Molina-Solana et al., 2017).

Competitor benchmarking is enhanced through data-driven comparison frameworks. Machine learning algorithms can analyze competitor data, identify performance metrics, and benchmark the organization's energy management against industry standards. This data-centric approach contributes to informed decision-making and strategic positioning (Woon et al., 2015).

In summary, the integration of data science into the Hybrid/Renewable Energy Management organization significantly augments test and simulation activities, analysis of results, and competitor benchmarking. Leveraging predictive modeling, advanced analytics, and machine learning algorithms enhances the efficiency, accuracy, and strategic decision-making capabilities within the organization. The adoption of data science methodologies positions the organization at the forefront of technological advancements in the field of Hybrid/Renewable Energy Management (Giaouris et al., 2013; Guelleh et al., 2020; Molina-Solana et al., 2017; Ozkan et al., 2020; Woon et al., 2015; Zell et al., 2008).

4.1.7.14 Mitigation Strategies for Challenges in Adoption of Data Science

Table 14 aligns Data Science use cases with business agility goals, identifies potential challenges, associated risks, and mitigation strategies for each specialized design process. The data science use cases outlined encompass various domains, each with its set of challenges and associated risk factors.

Table 14 Data Science Use Cases for the various process in Specialized Design sub function. Source : Author

Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
Artwork & Label Design	Image recognition for label layout design- Natural Language Processing (NLP) for artwork validation- Predictive modeling for market trend analysis	Lack of skilled workforce- Data quality and availability- Privacy and security concerns- Integration with existing systems	Inadequate expertise in AI and design tools- Inaccurate or incomplete label data- Unauthorized access to sensitive artwork- Incompatibility with existing design software	Provide training programs for AI tools and design software- Implement data quality checks and validation processes- Enforce strict access controls and encryption measures- Collaborate with IT for

Table 14 Data Science Use Cases for the various process in Specialized Design sub function. Source : Author				
Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
				seamless integration of AI tools with existing systems
Formulation Development	- Predictive modeling for optimal formula alternatives- Real-time monitoring and analytics for trial batches	- Lack of skilled workforce- Data quality and availability- Integration with existing systems- Privacy and security concerns	- Insufficient expertise in AI for formulation optimization- Inaccurate or incomplete formulation data- Unauthorized access to sensitive formulation data- Compatibility issues with existing data systems	- Conduct specialized training programs for AI in formulation development- Implement rigorous data quality checks and validation processes- Enforce strict access controls and encryption measures- Collaborate with IT for seamless

Table 14 Data Science Use Cases for the various process in Specialized Design sub function. Source : Author				
Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
				integration of AI tools with existing systems
Mechatronic Systems Concept Design	- Simulation and validation using machine learning- Predictive modeling for optimized components and configurations	- Lack of skilled workforce- Data quality and availability- Integration with existing systems- Privacy and security concerns	- Insufficient expertise in AI for mechatronic system optimization- Inaccurate or incomplete simulation data- Unauthorized access to sensitive design data- Compatibility issues with existing simulation tools	- Provide specialized training programs for AI in mechatronic system design- Implement rigorous data quality checks and validation processes- Enforce strict access controls and encryption measures- Collaborate

Table 14 Data Science Use Cases for the various process in Specialized Design sub function. Source : Author				
Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
				with IT for seamless integration of AI tools with existing systems
ETO Design Automation	- Parametric modeling using AI algorithms- Automated customer order analysis for design generation	- Lack of skilled workforce- Data quality and availability- Integration with existing systems- Privacy and security concerns	- Inadequate expertise in AI for parametric modeling- Inaccurate or incomplete customer order data- Unauthorized access to sensitive design data- Compatibility issues with existing design software	- Conduct specialized training programs for AI in parametric design- Implement rigorous data quality checks and validation processes- Enforce strict access controls and encryption measures- Collaborate with IT for

Table 14 Data Science Use Cases for the various process in Specialized Design sub function. Source : Author				
Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
				seamless integration of AI tools with existing systems
Packaging Design	- Predictive modeling for packaging concepts and performance- Simulation and digital prototyping using AI tools	- Lack of skilled workforce- Data quality and availability- Integration with existing systems- Privacy and security concerns	- Insufficient expertise in AI for packaging design optimization- Inaccurate or incomplete packaging data- Unauthorized access to sensitive design data- Compatibility issues with existing design and simulation tools	- Provide specialized training programs for AI in packaging design- Implement rigorous data quality checks and validation processes- Enforce strict access controls and encryption measures- Collaborate with IT for

Table 14 Data Science Use Cases for the various process in Specialized Design sub function. Source : Author				
Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
				seamless integration of AI tools with existing systems
Interior & Exterior Trim Design	- Collaboration analytics for successful OEM and supplier interactions- Predictive modeling for optimized design integrations	- Lack of skilled workforce- Data quality and availability- Integration with existing systems- Privacy and security concerns	- Insufficient expertise in AI for design collaboration optimization- Inaccurate or incomplete design collaboration data- Unauthorized access to sensitive design data- Compatibility issues with existing design tools and	- Provide specialized training programs for AI in design collaboration- Implement rigorous data quality checks and validation processes- Enforce strict access controls and encryption measures- Collaborate with IT for seamless

Table 14 Data Science Use Cases for the various process in Specialized Design sub function. Source : Author				
Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
			collaboration platforms	integration of AI tools with existing systems
Drive Assistant System Development & Autonomous Driving	- Simulation and optimization of driving algorithms using machine learning- Predictive analytics for safety component design and certification	- Lack of skilled workforce- Data quality and availability- Integration with existing systems- Privacy and security concerns	- Inadequate expertise in AI for driving algorithm simulation- Inaccurate or incomplete driving behavior data- Unauthorized access to sensitive safety component data- Compatibility issues with existing simulation tools and safety	- Provide specialized training programs for AI in driving algorithm simulation- Implement rigorous data quality checks and validation processes- Enforce strict access controls and encryption measures- Collaborate with IT for

Table 14 Data Science Use Cases for the various process in Specialized Design sub function. Source : Author				
Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
			certification processes	seamless integration of AI tools with existing systems
Battery Cell Design	- Virtual cell design and testing using machine learning- Predictive modeling for material properties and performance optimization	- Lack of skilled workforce- Data quality and availability- Integration with existing systems- Privacy and security concerns	- Inadequate expertise in AI for battery cell design optimization- Inaccurate or incomplete battery cell data- Unauthorized access to sensitive design and material data- Compatibility issues with existing design	- Conduct specialized training programs for AI in battery cell design- Implement rigorous data quality checks and validation processes- Enforce strict access controls and encryption measures- Collaborate with IT for

Table 14 Data Science Use Cases for the various process in Specialized Design sub function. Source : Author				
Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
			and simulation tools	seamless integration of AI tools with existing systems
Battery Module & Pack Design	- Simulation and optimization using machine learning for thermal management and NVH responses- Predictive modeling for performance evaluation	- Lack of skilled workforce- Data quality and availability- Integration with existing systems- Privacy and security concerns	- Inadequate expertise in AI for battery module and pack design optimization- Inaccurate or incomplete thermal and NVH data- Unauthorized access to sensitive design data- Compatibility issues with existing design	- Provide specialized training programs for AI in battery module and pack design- Implement rigorous data quality checks and validation processes- Enforce strict access controls and encryption measures- Collaborate with IT for

Table 14 Data Science Use Cases for the various process in Specialized Design sub function. Source : Author				
Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
			and simulation tools	seamless integration of AI tools with existing systems
Driving Behavior & Safety Simulation	- Simulation and prediction of driving behavior using machine learning- Predictive analytics for safety component design and simulation results optimization	- Lack of skilled workforce- Data quality and availability- Integration with existing systems- Privacy and security concerns	- Inadequate expertise in AI for driving behavior simulation- Inaccurate or incomplete driving behavior data- Unauthorized access to sensitive simulation results- Compatibility issues with existing simulation tools	- Provide specialized training programs for AI in driving behavior simulation- Implement rigorous data quality checks and validation processes- Enforce strict access controls and encryption measures- Collaborate with IT for

Table 14 Data Science Use Cases for the various process in Specialized Design sub function. Source : Author				
Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
				seamless integration of AI tools with existing systems
NVH & Acoustics Analysis	- Predictive modeling for driveline integration and acoustics optimization- Real-time analysis tools for noise and vibration issues	- Lack of skilled workforce- Data quality and availability- Integration with existing systems- Privacy and security concerns	- Inadequate expertise in AI for NVH and acoustics optimization- Inaccurate or incomplete NVH data- Unauthorized access to sensitive design and simulation data- Compatibility issues with existing analysis tools	- Provide specialized training programs for AI in NVH and acoustics analysis- Implement rigorous data quality checks and validation processes- Enforce strict access controls and encryption measures- Collaborate

Table 14 Data Science Use Cases for the various process in Specialized Design sub function. Source : Author				
Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
				with IT for seamless integration of AI tools with existing systems
Emission & Energy Management Analysis	- Predictive modeling for engine performance optimization and energy efficiency- Real-time analysis tools for emissions and energy consumption	- Lack of skilled workforce- Data quality and availability- Integration with existing systems- Privacy and security concerns	- Inadequate expertise in AI for emission and energy management optimization- Inaccurate or incomplete performance and efficiency data- Unauthorized access to sensitive analysis data- Compatibility issues with existing analysis tools	- Provide specialized training programs for AI in emission and energy management analysis- Implement rigorous data quality checks and validation processes- Enforce strict access controls and encryption measures- Collaborate

Table 14 Data Science Use Cases for the various process in Specialized Design sub function. Source : Author				
Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
				with IT for seamless integration of AI tools with existing systems
Hybrid/Renewable Energy Management	- Predictive modeling for power consumption optimization- Analysis of competitor benchmarking using AI tools	- Lack of skilled workforce- Data quality and availability- Integration with existing systems- Privacy and security concerns	- Inadequate expertise in AI for hybrid and renewable energy management- Inaccurate or incomplete power consumption data- Unauthorized access to sensitive analysis data- Compatibility issues with	- Provide specialized training programs for AI in hybrid and renewable energy management- Implement rigorous data quality checks and validation processes- Enforce strict access controls and encryption measures-

Process	Data Science Use Cases	Challenges	Risk	Mitigation Strategies
			existing analysis tools	Collaborate with IT for seamless integration of AI tools with existing systems

Table 14 Data Science Use Cases for the various process in Specialized Design sub function. Source : Author

Table 14 provides a comprehensive overview of the application of AI use cases in each specialized design process, aligned with business agility goals, potential challenges, associated risks, and mitigation strategies. The integration of AI enhances agility by improving decision-making, process speed, and resource adaptability across diverse design functions. Addressing challenges through training, data quality measures, and collaboration with IT ensures a successful implementation of AI in specialized design contexts.

Incorporating data science and AI into specialized design functions revolutionizes product development by enhancing efficiency, accuracy, and adaptability. Each design process benefits from specific AI use cases tailored to improve various aspects of the design lifecycle.

Artwork & Label Design: AI aids in creating visually appealing labels by leveraging image recognition and NLP. Predictive modeling ensures designs align with market trends, fostering improved behavioral awareness. However, challenges such as a lack of skilled workforce and data quality issues may hinder implementation. Mitigation strategies include training programs and rigorous data quality checks.

Formulation Development: Predictive modeling optimizes formula alternatives, accelerating decision-making and dynamic processes. Real-time monitoring during trial batches enhances behavioral awareness. Overcoming challenges related to skilled workforce and data quality requires targeted training and rigorous data validation processes.

Mechatronic Systems Concept Design: Simulation and predictive modeling optimize component configurations, aligning with goals of augmented decision-making and dynamic processes. The lack of skilled workforce and integration challenges necessitate training and collaborative efforts with IT for seamless integration.

ETO Design Automation: Parametric modeling through AI expedites customized design generation, promoting dynamic processes. Augmented decision-making benefits from automated customer order analysis. Challenges like a lack of skilled workforce and privacy concerns are addressed through training and strict access controls.

Packaging Design: Predictive modeling guides packaging concepts, improving situational awareness of market trends. Challenges like data quality and privacy concerns are mitigated through specialized training and encryption measures.

Interior & Exterior Trim Design: Collaboration analytics and predictive modeling optimize design integrations, aligning with goals of behavioral awareness and dynamic processes. Challenges related to skilled workforce and data quality require training and validation processes.

Drive Assistant System Development & Autonomous Driving: Simulation and optimization of driving algorithms using AI contribute to improved situational awareness and dynamic processes. Addressing challenges involves specialized training and collaboration with IT for seamless integration.

Battery Cell Design: Virtual testing and predictive modeling optimize battery cell design, enabling augmented decision-making. Challenges are mitigated through specialized training and rigorous data quality checks.

Battery Module & Pack Design: Simulation and optimization using AI contribute to augmented decision-making and dynamic processes. Addressing challenges involves specialized training and collaboration with IT for seamless integration.

Driving Behavior & Safety Simulation: Simulation and prediction using machine learning enhance behavioral awareness and decision-making. Challenges related to skilled workforce and data quality require training and validation processes.

NVH & Acoustics Analysis: Predictive modeling optimizes acoustics, improving behavioral awareness and decision-making. Challenges such as a lack of skilled workforce are addressed through training and collaboration with IT.

Emission & Energy Management Analysis: Predictive modeling for energy efficiency aligns with business agility goals. Challenges related to skilled workforce and data quality are addressed through training and validation processes.

Hybrid/Renewable Energy Management: Predictive modeling optimizes power consumption, contributing to improved decision-making. Challenges are mitigated through specialized training and collaboration with IT. In conclusion, the integration of data science and AI in specialized design functions is pivotal for achieving business agility goals. While challenges exist, strategic mitigation strategies such as targeted training, rigorous data validation, and collaboration with IT ensure successful implementation and unlock the full potential of AI in specialized design contexts.

4.2 Mitigation Strategies for Challenges in Adoption of Data Science in Manufacturing Planning

Within Manufacturing Planning, the integration of data science offers substantial opportunities for optimizing various critical activities. This section explores how data science can be effectively applied to manufacturing process planning, management of manufacturing resources, production simulation, and specialized manufacturing process planning. This section briefly discusses on how Data Science can support the below sub functions of manufacturing planning organization.

- Manufacturing Process Planning
- Manufacturing Resources
- Production Simulation
- Specialized Manufacturing Process Planning

4.2.1 Mitigation Strategies for Challenges in Adoption of Data Science in Manufacturing Process Planning

This section attempts to deep dive into the data science use cases of manufacturing process planning function and the last section summarize the different use cases as well as discuss the mitigation strategies for the challenges in adopting data science in each of the activities of the manufacturing process planning function as shown in *Figure 107*. Integration of data science into the Manufacturing Process Planning sub-function offers opportunities to enhance various activities. This section explores how data science can be applied to Manufacturing Configuration Management, Manufacturing Assembly Process Planning, Part Fabrication Planning and CNC Programme Management, Part Inspection & Metrology Planning, Virtual Machine for CNC Program Validation, Production Quality and Inspection Planning, Robotics Planning and Simulation, Formulated Product Quality Control [Lab Info Mgt Sys], Production Process Concept & Design, Manufacturing Concept Planning, and Chemical Process Design.

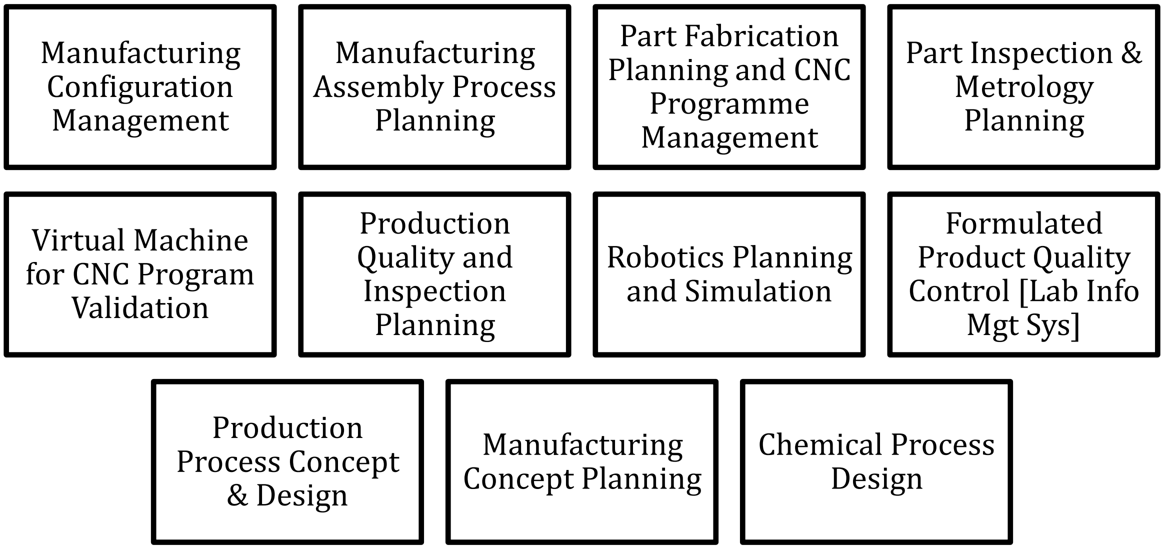

Figure 108 Manufacturing Process Planning Sub Functions. Source: Author

4.2.1.1 Manufacturing Configuration Management

The integration of data science into the Manufacturing Configuration Management activity within the Manufacturing Process Planning sub-function is instrumental in enhancing the efficiency and effectiveness of manufacturing planning processes. This section delves into how data science can be applied to activities as shown in *Figure 109***,** involving the definition of manufacturing architecture and configuration, development of manufacturing solutions, planning of production material and logistics, and validation and release of manufacturing solutions.

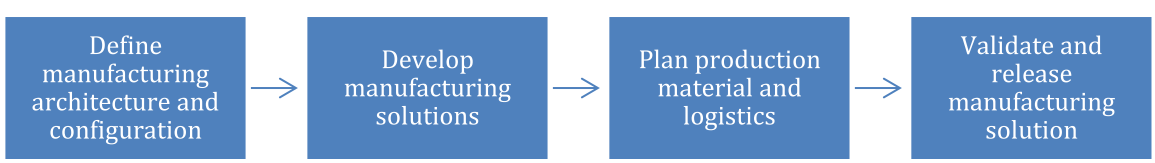

Figure 110 Typical Manufacturing Configuration Management Process Flow. Source: Author

Data science plays a pivotal role in defining manufacturing architecture and configuration by leveraging historical data and contextual information. Machine learning algorithms can analyze past configurations, production parameters, and design specifications to recommend optimal manufacturing architectures, ensuring a more informed and tailored configuration process.

The development of manufacturing solutions benefits from data-driven approaches. Predictive modeling, including machine learning, can analyze historical production data and design specifications to propose optimized manufacturing solutions. This data-centric approach enhances the precision and efficiency of the solution development phase.

Planning production material and logistics is streamlined through data science applications. Predictive analytics models can analyze material consumption patterns, supplier performance, and logistics data to optimize production planning. This ensures that material availability aligns with production requirements, minimizing delays and improving overall logistics efficiency.

The validation and release of manufacturing solutions are facilitated by data science-driven validation processes. Machine learning models can analyze solution data for accuracy and completeness, identifying potential issues or discrepancies. This ensures that manufacturing solutions align with design specifications and quality standards before release.

The infusion of data science into Manufacturing Configuration Management activities within Manufacturing Process Planning contributes to more precise and efficient manufacturing planning processes. From recommending optimal configurations and developing tailored solutions to optimizing material planning and validating solutions, data science ensures a data-driven and informed approach. This holistic integration enhances the overall effectiveness of manufacturing planning within the manufacturing process (Arantes et al., 2018; Farooqui et al., 2020; Fisher et al., 2020; Kibira et al., 2015; Vazan et al., 2017).

4.2.1.2 Manufacturing Assembly Process Planning

In the realm of Manufacturing Planning, specifically within the Manufacturing Process Planning function, the incorporation of data science into the Manufacturing Assembly Process Planning activity shown in *Figure 111***,** presents opportunities for enhanced efficiency and decision-making. This section explores the application of data science in activities involving the definition of assembly processes, work operation details, part and resource assignments, plant-specific processes, standard processes and operations, process time standards and libraries, cost analysis, authoring work instructions, and managing production releases.

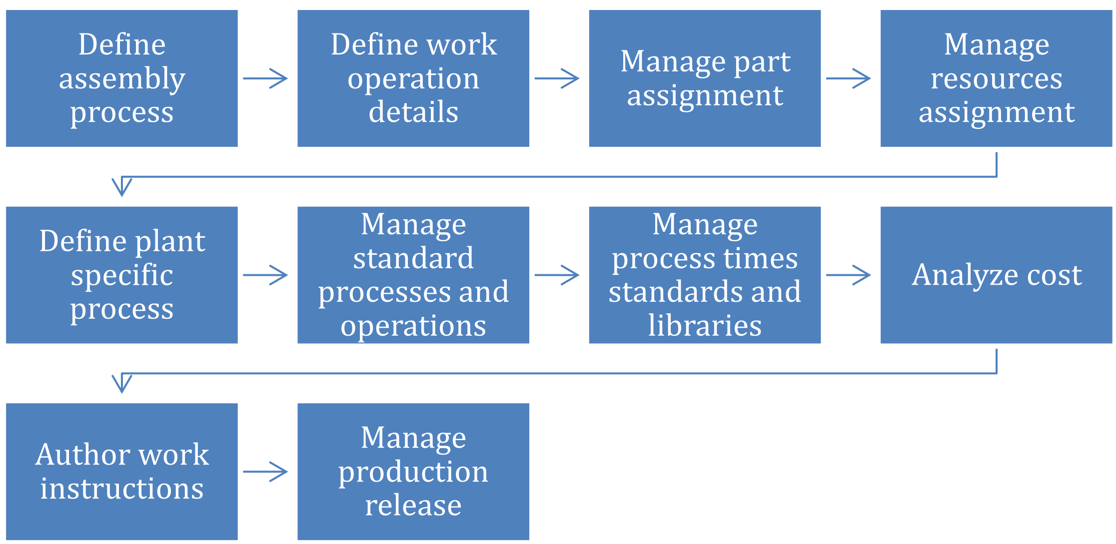

Figure 112 Typial Manufacturing Assembly Process Planning Process Flow. Source: Author

Data science plays a pivotal role in defining assembly processes by analyzing historical process data and optimizing parameters for improved efficiency. Machine learning models can suggest optimal assembly sequences and configurations based on past data, ensuring the most effective and streamlined processes.

The definition of work operation details benefits from data science through predictive modeling. By analyzing historical work operation data, machine learning algorithms can assist in defining operation details, optimizing resource allocation, and ensuring efficient task execution.

Managing part and resource assignments is facilitated by data science through automated optimization algorithms. These algorithms analyze part specifications, resource capabilities, and historical assignment data to suggest optimal combinations, minimizing bottlenecks and improving overall assembly efficiency.

Plant-specific processes are refined with data science by analyzing plant-specific parameters and historical performance data. Machine learning models can suggest adjustments to processes based on specific plant conditions, ensuring alignment with plant-specific requirements and constraints.

Standard processes and operations management are enhanced by data-driven systems. Predictive analytics models can analyze historical data to optimize standard processes, improving consistency and reducing variability in manufacturing operations.

Process time standards and libraries are streamlined with data science by developing algorithms that assess historical process times and standards. This ensures that time standards are accurately set, reflecting the realistic time requirements for each process.

Cost analysis benefits from data science by employing predictive models that consider various cost factors. By analyzing historical cost data, machine learning algorithms can assist in estimating costs for different assembly processes, aiding in budgeting and decision-making.

Authoring work instructions is facilitated by data science through automated content generation. Natural Language Processing (NLP) algorithms can analyze historical work instruction data, generating clear and concise instructions that align with industry best practices.

Managing production releases is optimized with data science by developing automated release management systems. Machine learning models can assess various release factors, historical release data, and market conditions to suggest optimal release timings and strategies.

In conclusion, the integration of data science into the Manufacturing Assembly Process Planning activity within Manufacturing Process Planning contributes to more efficient assembly processes, optimized resource utilization, and informed decision-making. Leveraging machine learning, predictive analytics, and automated systems, data science enhances various facets of the assembly planning process, fostering a data-driven and streamlined approach to manufacturing operations. This data-centric approach aligns with the broader goals of Manufacturing Planning, ensuring optimal efficiency and effectiveness throughout the manufacturing lifecycle (Kretschmer et al., 2017; Qin & Dong, 2020; Rychtyckyj et al., 2007; Vazan et al., 2017; Wallis et al., 2014).

4.2.1.3 Part Fabrication Planning and CNC programs Management

In the realm of Manufacturing Planning, specifically focusing on the Part Fabrication Planning and CNC Programs Management activity, data science plays a pivotal role in optimizing various tasks shown in *Figure 113*. This section explores how data science can be effectively applied to activities such as defining part fabrication processes, specifying tools and fixtures, making machine assignments, developing machining programs, programming tool paths, simulating and validating tool paths, developing part manufacturing documentation, and validating/releasing NC programs and routings.

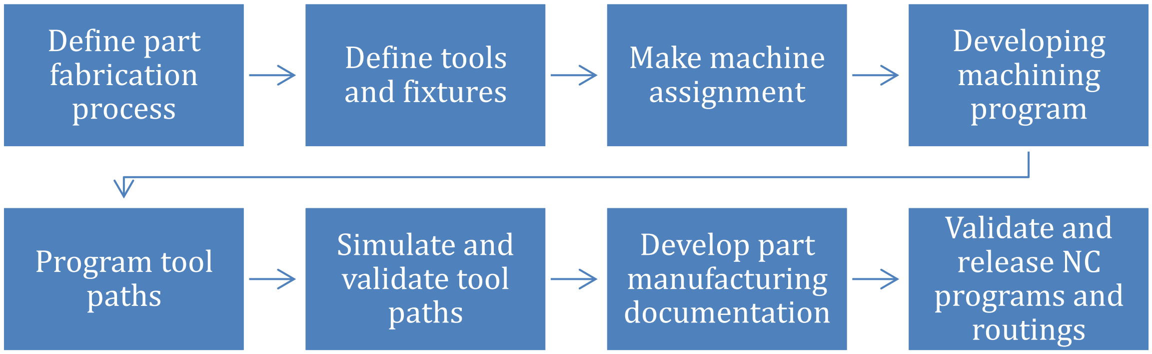

Figure 114 Part Fabrication Planning and CNC programs Management Process Flow. Source: Author

Data science contributes to defining part fabrication processes by analyzing historical data and manufacturing specifications. Machine learning algorithms can identify patterns and recommend optimal fabrication processes based on part characteristics, production requirements, and past performance data.

For defining tools and fixtures, data science leverages optimization algorithms to determine the most suitable tools and fixtures for a given part. Historical data on tool performance and fixture effectiveness can be used to guide decisions, ensuring efficient and effective fabrication processes.

Making machine assignments benefits from data science through predictive modeling. Machine learning algorithms can analyze machine capabilities, workload, and historical assignment data to optimize machine assignments for specific parts, improving overall production efficiency.

Developing machining programs is enhanced by data-driven systems. Machine learning algorithms can analyze past program data to suggest improvements, optimize tool selections, and ensure that programs align with fabrication specifications.

Programming tool paths can benefit from data science by utilizing algorithms that optimize paths based on historical performance data. This improves the efficiency of tool movement, reduces machining time, and minimizes errors in the fabrication process.

Simulating and validating tool paths involve data-driven simulations. Machine learning models can predict potential issues, such as collisions or inefficiencies, during the simulation process, allowing for proactive adjustments before the actual fabrication begins.

Developing part manufacturing documentation is streamlined through data science. Natural Language Processing (NLP) algorithms can automate the creation of documentation by extracting relevant information from design specifications and historical documentation, ensuring accuracy and completeness.

Validating and releasing NC programs and routings benefit from automated validation tools driven by data science. Machine learning models can assess the conformity of programs and routings with established standards, minimizing errors and ensuring that only validated programs proceed to the manufacturing phase.

In conclusion, the integration of data science into Part Fabrication Planning and CNC Programs Management activities within the broader Manufacturing Planning framework contributes to improved efficiency, accuracy, and optimization in the manufacturing process. From optimizing tool paths to automating documentation creation, data science enhances decision-making, reduces errors, and ensures a more streamlined and effective part fabrication and CNC programs management process (Altintas et al., 2014; Deng et al., 2021; Liu et al., 2009; Mohamed et al., 2013; Safaieh et al., 2013).

4.2.1.4 Part Inspection & Metrology Planning

In the intricate domain of Manufacturing Planning, the integration of data science into the specific activity shown in *Figure 115* of "Part Inspection & Metrology Planning" holds promising potential. This section delves into how data science can be effectively employed in the multifaceted tasks of developing test and inspection plans, managing inspection equipment, generating metrology programs, and validating and releasing these programs.

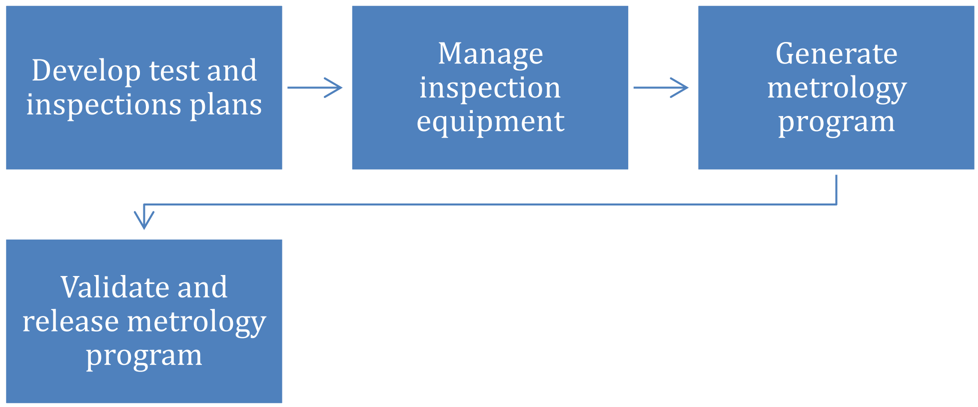

Figure 116 Typical Part Inspection & Metrology Planning Process Flow. Source: Author

Data science enhances the development of test and inspection plans by analyzing historical inspection data and part specifications. Machine learning models can identify patterns, aiding in the formulation of comprehensive plans that are adapted to the specific characteristics and requirements of each part.

Managing inspection equipment is streamlined through data-driven approaches. Predictive analytics models can assess equipment performance, predict maintenance needs, and optimize the scheduling of inspections. This ensures that inspection equipment is consistently available and operational.

The generation of metrology programs benefits from data science by automating the process. Machine learning algorithms can analyze part geometry, historical metrology data, and tolerance requirements to generate programs tailored for efficient and accurate measurements.

Validating and releasing metrology programs are facilitated by data-driven quality assurance processes. Machine learning models can assess the compatibility of metrology programs with part specifications, identifying potential issues or deviations. This data-centric validation ensures the reliability and accuracy of metrology programs before their release.

In summary, the infusion of data science into Part Inspection & Metrology Planning activities within the broader context of Manufacturing Process Planning leads to improved test and inspection plans, streamlined equipment management, automated program generation, and robust program validation. This data-driven approach optimizes manufacturing processes, enhances quality control, and contributes to the overall efficiency of manufacturing planning (Gudmundsson & Shanthikumar, 2005; Kok et al., 2016; Lukic & Lukic, 2013; Stojadinovic et al., 2021; Ward et al., 2010).

4.2.1.5 Virtual Machine for CNC Program Validation

Within the domain of Manufacturing Planning, the application of data science in the "Virtual Machine for CNC Program Validation" activity shown in *Figure 117*, holds the potential to optimize manufacturing processes and enhance overall efficiency. This section explores how data science can be integrated into activities such as supporting post processor development, simulating, and validating numerical control programs, providing OEM support for end customers, and conducting machine user training.

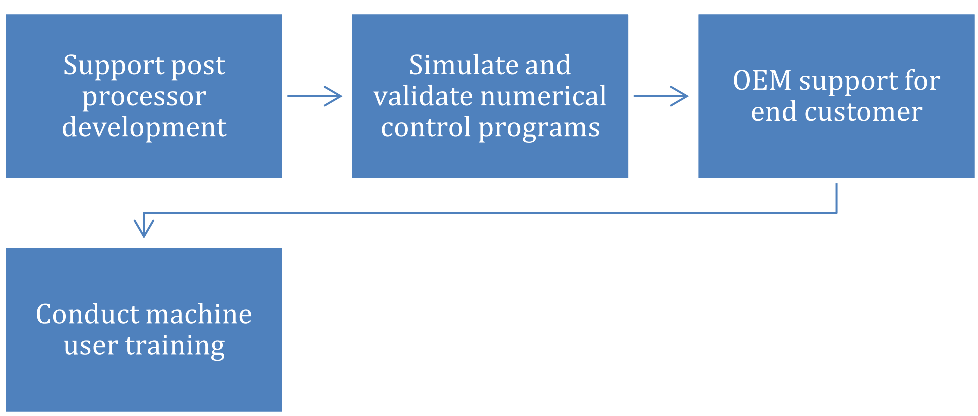

Figure 118 Typical Virtual Machine for CNC Program Validation Process Flow. Source: Author

Supporting Post Processor Development: Data science contributes to post processor development by analyzing historical data on machine specifications and programming requirements. Machine learning algorithms can identify patterns in post processor development, leading to the creation of more efficient and accurate post processors that align with specific machine capabilities.

Simulating and Validating Numerical Control Programs: The simulation and validation of numerical control programs benefit from data science-driven predictive modeling. Machine learning models can analyze historical CNC program data, machine performance data, and material characteristics to predict potential issues in the program. This proactive approach ensures that programs are thoroughly validated before actual manufacturing processes, minimizing errors, and improving overall program reliability.

OEM Support for End Customer: Data science plays a role in providing OEM support by leveraging predictive analytics. Machine learning models can predict potential issues in CNC programs or machine operations based on historical data. This enables OEMs to offer proactive support to end customers, addressing concerns before they impact the manufacturing process.

Conducting Machine User Training: Machine user training is enhanced by data science through the development of personalized training programs. By analyzing user performance data and learning patterns, machine learning algorithms can tailor training modules to individual user needs, optimizing the learning experience and ensuring proficiency in CNC programming and machine operation.

In summary, the integration of data science into the Virtual Machine for CNC Program Validation activity within Manufacturing Process Planning brings about improvements in post processor development, CNC program simulation and validation, OEM support, and machine user training. This data-centric approach contributes to the optimization of manufacturing processes, increased reliability in CNC programming, and enhanced support mechanisms for both manufacturers and end customers (García et al., 2014; Luo et al., 2010; Sun, 2002; Yeung et al., 2006).

4.2.1.6 Production Quality and Inspection Planning

Within the Manufacturing Planning function, the Manufacturing Process Planning sub-function of Production Quality and Inspection Planning involves various activities shown in *Figure 119* crucial for ensuring quality in the production process. This section explores how data science can be integrated into activities such as developing control plans, test, and inspection plans, managing inspection equipment, defining, and acquiring inspection points, monitoring gage calibration, developing quality reports and documentation, and validating and releasing inspection plans.

Data science aids in the development of control plans by analyzing historical quality data. Machine learning models can identify patterns and potential risks, assisting in the formulation of robust control plans that address historical issues and proactively mitigate risks.

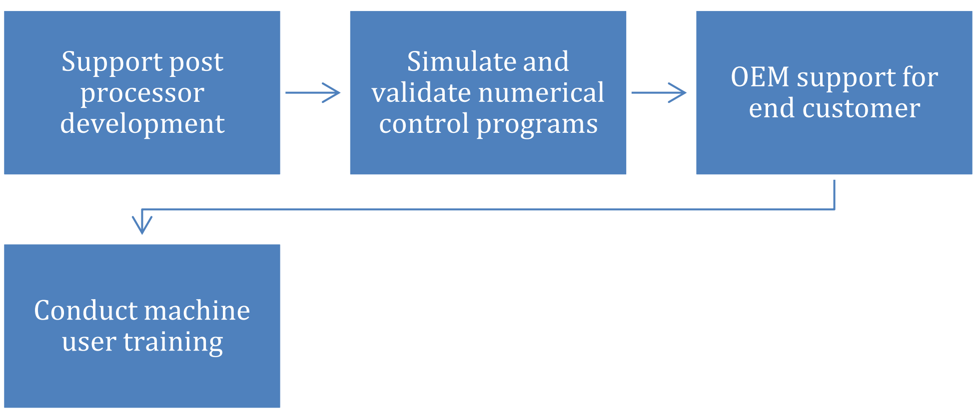

Figure 120 Typical Production Quality and Inspection Planning Process Flow. Source: Author

For developing test and inspection plans, data science leverages predictive analytics to assess the criticality of components. By considering factors such as historical defect rates, supplier performance, and production variability, data-driven models help optimize test and inspection plans for maximum effectiveness.

In managing inspection equipment, data science supports predictive maintenance strategies. Algorithms analyze equipment performance data, predicting potential failures and optimizing maintenance schedules. This ensures that inspection equipment is in optimal condition, reducing downtime and improving overall efficiency.

The definition and acquisition of inspection points benefit from data science through automated data tagging. Natural Language Processing (NLP) algorithms can analyze textual descriptions and specifications, aiding in the consistent definition and tagging of inspection points for standardized and accurate reporting.

The management and monitoring of gage calibration are streamlined with data-driven systems. Predictive models assess calibration data, predicting when calibrations are due and optimizing calibration schedules. This proactive approach ensures that measurement instruments are consistently accurate.

Data science facilitates the development of quality reports and documentation by automating data analysis. Machine learning algorithms can process large datasets, identifying trends, correlations, and outliers for inclusion in comprehensive quality reports.

The validation and release of inspection plans are enhanced through data-driven validation processes. Predictive models assess the viability of inspection plans, considering historical data on inspection effectiveness and recommending adjustments to optimize plan performance.

In conclusion, the integration of data science into the Production Quality and Inspection Planning activities of Manufacturing Process Planning ensures a data-driven and proactive approach to quality assurance. From developing control plans to validating and releasing inspection plans, data science contributes to more effective decision-making, risk mitigation, and continuous improvement in the manufacturing process (Cai-yan & You-fa, 2009; Qin & Dong, 2020; Sajid et al., 2021; Wang et al., 2023; West et al., 2021).

4.2.1.7 Robotics Planning and Simulation

Within the Manufacturing Planning function, the Robotics Planning and Simulation activity shown in *Figure 121***,** plays a crucial role in optimizing manufacturing processes. This section explores how data science can be applied to activities involving planning robotic processes, executing robotics simulations, planning gripper, fixture, and tools, developing robot paths and OLP commands, and integrating robots into manufacturing cells.

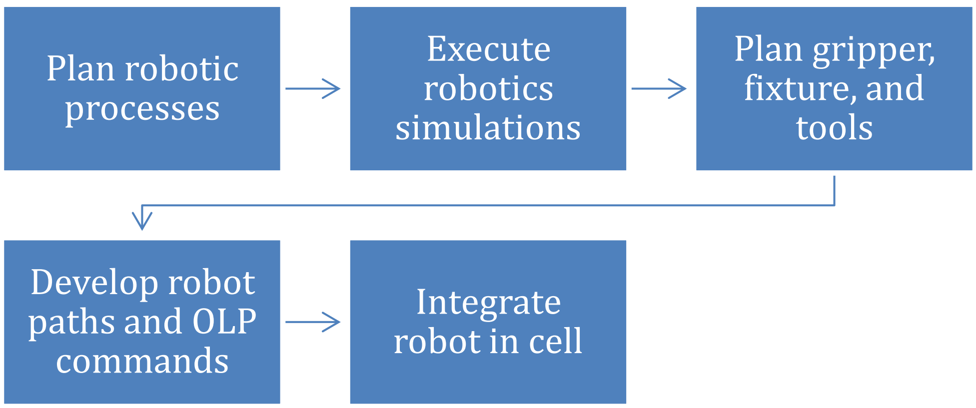

Figure 122 Typical Robotics Planning and Simulation Process Flow. Source: Author

Data science enhances the planning of robotic processes by analyzing historical data on manufacturing requirements and resource utilization. Predictive modeling can assist in identifying optimal robotic configurations, minimizing production times, and improving overall process efficiency.

Executing robotics simulations benefits from data-driven approaches. Machine learning algorithms can simulate various scenarios based on historical data, allowing for the identification of potential bottlenecks, resource constraints, and areas for improvement in the manufacturing process.

Planning gripper, fixture, and tools is optimized through data science. Predictive analytics models can analyze historical data on tool performance, material properties, and production requirements to recommend the most suitable gripper, fixture, and tools for a specific manufacturing task.

Developing robot paths and OLP commands is streamlined by leveraging data science. Machine learning algorithms can analyze past robot paths, identify optimal trajectories, and generate Offline Programming (OLP) commands that minimize cycle times and enhance precision in manufacturing processes.

Integrating robots into manufacturing cells benefits from data-centric methodologies. Predictive modeling can assess the compatibility of robots with existing manufacturing infrastructure, considering factors such as space constraints and resource availability. This ensures seamless integration and minimizes disruptions in the manufacturing environment.

In summary, the integration of data science into the Robotics Planning and Simulation activity of Manufacturing Process Planning enhances various facets of the manufacturing process. From optimizing robotic configurations and simulating scenarios to recommending tools and streamlining robot integration, data science contributes to efficient and data-driven decision-making within the manufacturing planning domain (Ngo et al., 2005; Proctor et al., 2016; Vendrell et al., 2001; Xiao et al., 2004).

4.2.1.8 Formulated Product Quality Control

In the domain of Manufacturing Process Planning, specifically within the sub-function of Formulated Product Quality Control using a Lab Information Management System (LIMS), data science can play a pivotal role in optimizing various activities. This section explores how data science can be applied to activities shown in *Figure 123***,** such as registering raw material quality data, performing resource planning, managing, and analyzing trending and charting, overseeing laboratory equipment, registering product experiments and trials, executing product sample planning, registering production quality data, managing stability and shelf-life studies, and registering new product development data.

Registering Raw Material Quality Data: Data science contributes to the registration of raw material quality data by implementing automated data capture and processing systems. Machine learning models can analyze historical raw material data, identifying patterns and trends to improve the accuracy of quality data registration.

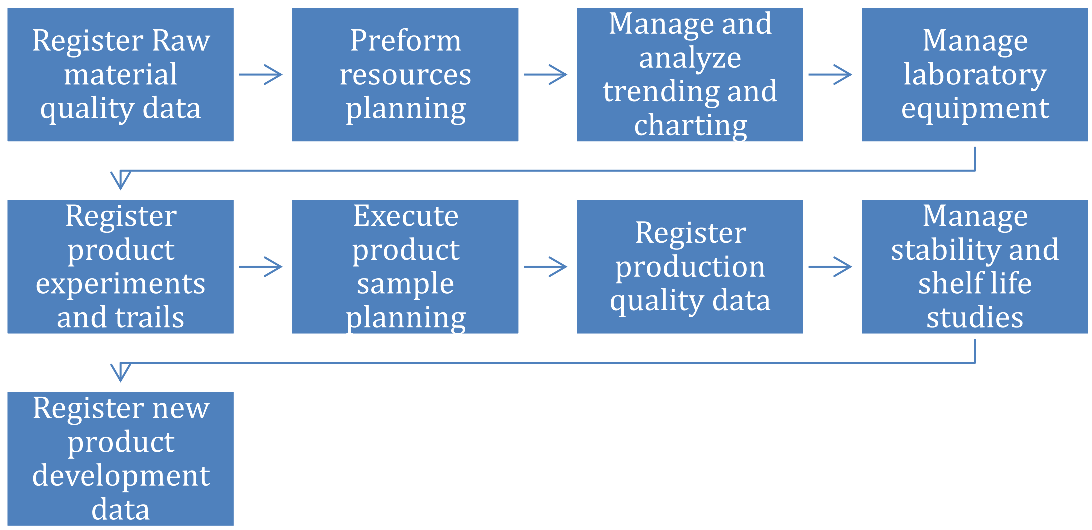

Figure 124 Typical Formulated Product Quality Control Process Flow. Source: Author

Performing Resources Planning: Data science enables efficient resource planning by analyzing production data, demand forecasts, and resource availability. Optimization algorithms and predictive modeling can aid in determining the optimal allocation of resources, ensuring that the manufacturing process is well-planned and resource-efficient.

Managing and Analyzing Trending and Charting: Data science techniques such as statistical analysis and machine learning can be employed to manage and analyze trending and charting data. These methods provide insights into the quality trends over time, allowing for proactive quality control measures and continuous improvement.

Managing Laboratory Equipment: Predictive maintenance algorithms powered by data science can be applied to manage laboratory equipment efficiently. By analyzing equipment usage patterns and performance data, organizations can schedule maintenance activities before equipment failures occur, minimizing downtime.

Registering Product Experiments and Trials: Data science supports the registration of product experiments and trials by automating data entry processes and ensuring consistency. NLP algorithms can process experiment documentation, extracting key information and improving the accuracy and efficiency of data registration.

Executing Product Sample Planning: Optimization algorithms can be utilized for product sample planning, considering factors such as sample size, frequency, and testing requirements. Data science ensures that sample planning is aligned with quality control objectives and regulatory standards.

Registering Production Quality Data: Automated data registration processes driven by data science enhance the accuracy and speed of registering production quality data. Real-time data capture and analytics contribute to a more comprehensive understanding of product quality during the production process.

Managing Stability and Shelf-Life Studies: Data science aids in managing stability and shelf-life studies by analyzing data related to product stability over time. Predictive models can assess the impact of various factors on product stability, facilitating informed decisions regarding shelf life and storage conditions.

Registering New Product Development Data: Data science supports the registration of new product development data by automating data entry and ensuring consistency in documentation. Machine learning models can analyze historical development data, providing insights for future product development processes.

In summary, the integration of data science into Formulated Product Quality Control activities within the Manufacturing Process Planning sub-function enhances various facets of quality management. From optimizing resource planning and equipment maintenance to automating data registration and analyzing trends, data science ensures a more efficient and informed approach to quality control in the manufacturing domain (Ansari-Ch. et al., 2011; Gemenetzi, 2015; Reitmeier & Paetzold, 2011; Wang et al., 2007; West et al., 2021).

4.2.1.9 Production Process Concept & Design

In the realm of Manufacturing Planning, the integration of data science into the Production Process Concept & Design activities within the Manufacturing Process Planning sub-function offers significant potential for optimizing processes and enhancing decision-making. This section explores how data science can be applied to activities shown in figure *125*, involving the development of process concepts, definition of production processes, specification of process details, management of standard processes and operations, handling of process time standards and libraries, and the release of production processes.

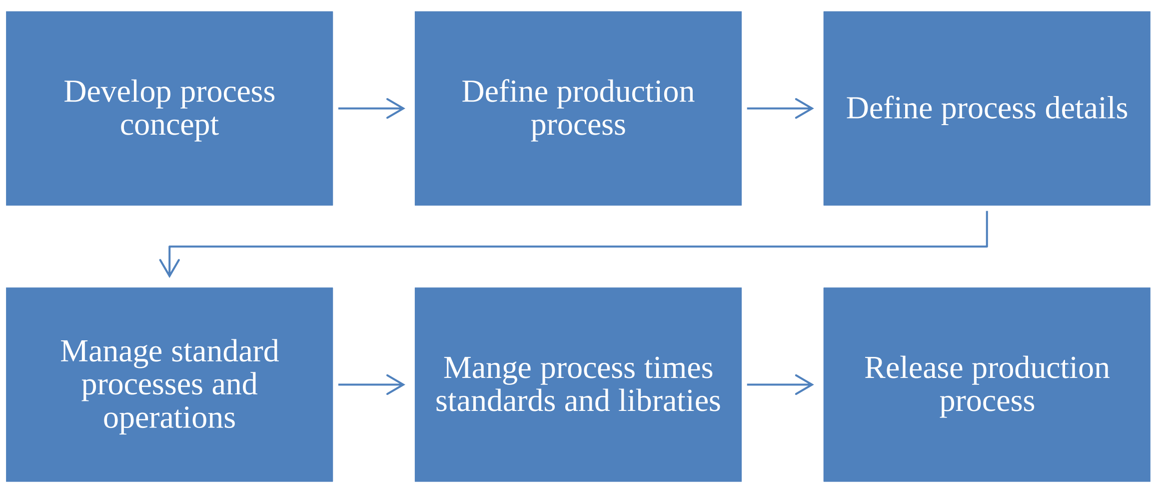

Figure 126 Typical Production Process Concept & Design Process Flow. Source: Author

Data science contributes to the development of process concepts by analyzing historical data and industry trends. Machine learning models can identify patterns, suggesting innovative process concepts that align with past successes and current market demands.

Defining production processes benefits from data science by incorporating optimization algorithms. These algorithms analyze various parameters such as cost, efficiency, and resource utilization, aiding in the selection of the most suitable production processes based on historical performance data.

Specifying process details is streamlined through data-driven decision-making. Predictive analytics models can assess the impact of different details on the overall process, offering insights into the optimal configuration of parameters such as equipment settings, materials, and production sequences.

The management of standard processes and operations is enhanced by data science through automated categorization and optimization. Machine learning algorithms can classify processes based on historical data, ensuring standardized approaches, and recommend improvements to increase efficiency.

Handling process time standards and libraries benefits from data science-driven analytics. Predictive models can estimate and optimize process times based on historical performance, enabling more accurate planning and resource allocation.

Releasing production processes are facilitated through data-driven validation processes. Automated algorithms can analyze proposed processes against predefined standards, ensuring compliance and mitigating risks before formal release.

In conclusion, the integration of data science into Production Process Concept & Design activities within Manufacturing Process Planning enhances various facets of the manufacturing planning lifecycle. From innovative concept development and process definition to optimized details, standardized operations, and accurate time standards, data science ensures a more informed and efficient approach to manufacturing process planning. This data-centric methodology contributes to improved decision-making and streamlined processes within the broader context of manufacturing planning (Khan et al., 2023; Qin & Dong, 2020; Salgado et al., 2018; Shcherbakov et al., 2014; Vazan et al., 2011).

4.2.1.10 Manufacturing Concept Planning

In the domain of Manufacturing Planning, specifically within the Manufacturing Process Planning sub-function, the utilization of data science in Manufacturing Concept Planning activities holds significant potential. This section explores how data science can be effectively employed in the various facets of this activity shown in *Figure 127*, encompassing the development of assembly process concepts, definition of production technologies, creation of part manufacturing concepts, formulation of manufacturing resource concepts, configuration of production concepts, management of concept alternatives and decision processes, calculation of resource investments, analysis of capacity availability, and computation of manufacturing costs.

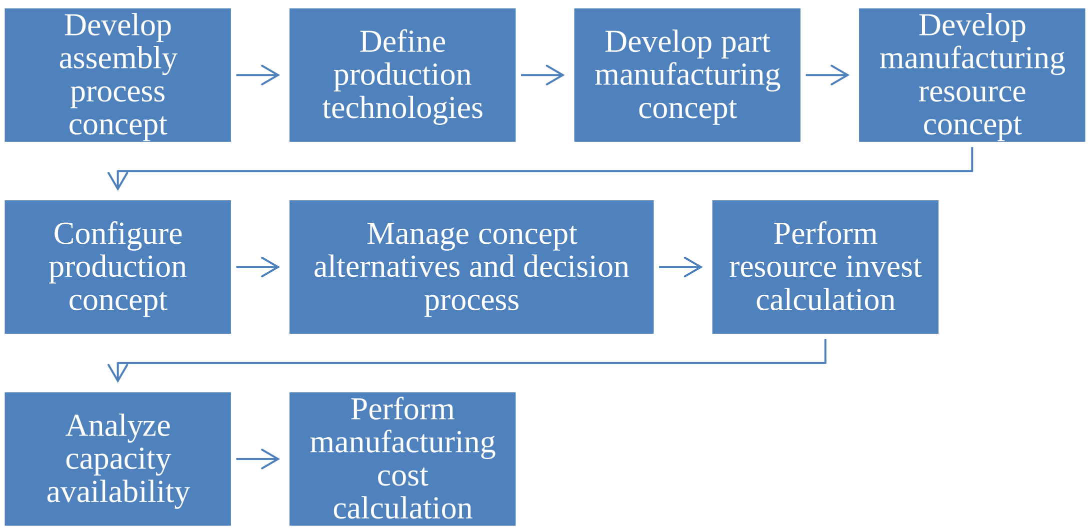

Figure 128 Typical Manufacturing Concept Planning Process Flow. Source: Author

Data science aids in developing assembly process concepts through the analysis of historical assembly data and simulation modeling. Machine learning algorithms can identify optimal assembly sequences and predict potential bottlenecks, ensuring a streamlined and efficient assembly process.

In defining production technologies, data science leverages predictive modeling to assess the performance of different technologies. Algorithms can analyze historical technology data, industry trends, and cost implications, providing insights into the most suitable production technologies for a given scenario.

For the development of part manufacturing concepts, data science utilizes generative modeling and optimization algorithms. These algorithms consider part specifications, material characteristics, and historical manufacturing data to propose innovative and efficient part manufacturing concepts.

The formulation of manufacturing resource concepts is enhanced through data-driven decision support systems. Machine learning models can analyze resource utilization patterns, recommending the optimal allocation of manufacturing resources based on historical performance and current demand.

In configuring production concepts, data science contributes by optimizing production configurations through simulation and scenario analysis. Predictive analytics models can evaluate different production configurations, considering factors such as lead times, resource utilization, and cost efficiency.

The management of concept alternatives and decision processes is facilitated by data science-driven decision support systems. These systems utilize historical data and real-time information to assist decision-makers in evaluating alternatives, considering various criteria such as cost, resource availability, and production timelines.

Performing resource investment calculations benefits from data science through cost modeling and optimization algorithms. Machine learning models can analyze historical investment data, market trends, and resource efficiency metrics to predict and optimize resource investments for manufacturing concepts.

Analyzing capacity availability is enhanced by data science through real-time monitoring and predictive modeling. Algorithms can analyze current capacity utilization, predict future demand, and recommend adjustments to ensure optimal capacity availability throughout the manufacturing process.

Performing manufacturing cost calculations is streamlined through data science-driven cost modeling. Predictive analytics models can consider various cost factors, such as material costs, labor costs, and overhead expenses, providing accurate and dynamic manufacturing cost calculations.

In summary, the integration of data science into Manufacturing Concept Planning activities within the Manufacturing Process Planning sub-function contributes to the optimization of assembly processes, technology selection, part manufacturing, resource allocation, production configurations, decision-making processes, resource investments, capacity analysis, and cost calculations. This data-centric approach enhances the efficiency, accuracy, and agility of manufacturing planning processes, fostering informed decision-making and overall improvement in manufacturing operations (Filz et al., 2020; Kibira et al., 2015; Perzyk et al., 2011; Sajid et al., 2021; Vazan et al., 2017).

4.2.1.11 Chemical Process Design

In the realm of Manufacturing Process Planning, specifically focusing on the Chemical Process Design activity, the integration of data science introduces opportunities for enhanced precision and efficiency. This section delves into how data science methodologies can be applied to activities shown in *Figure 129***,** involving the definition of production processes, specification of process parameters, development of work instructions, management of process times and routines libraries, and validation and release of production processes.

Data science contributes to the definition of production processes by leveraging historical process data and contextual information. Machine learning models can analyze past production processes, identifying patterns and optimizing the definition of new processes for increased efficiency and effectiveness.

The specification of process parameters benefits from data science through the application of optimization algorithms. By considering various parameters, historical performance data, and desired outcomes, data science can suggest optimal process parameter configurations, ensuring the desired quality and efficiency in the chemical manufacturing process.

The development of work instructions is streamlined with the use of natural language processing (NLP) algorithms. These algorithms can analyze existing work instructions, identify patterns, and suggest improvements or generate new instructions based on historical data, ensuring clarity and consistency in communication.

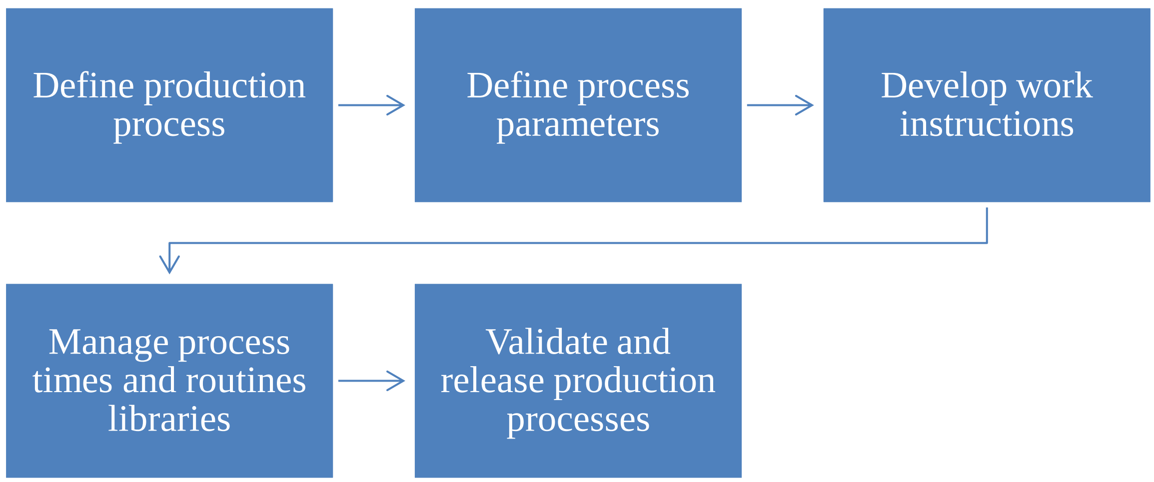

Figure 130 Typical Chemical Process Design Process Flow. Source: Author

Managing process times and routines libraries is enhanced by data science-driven automation. Predictive analytics models can analyze historical data to optimize process times, improve routine efficiency, and reduce variability, contributing to a more streamlined and predictable manufacturing process.

Validation and release of production processes benefit from data science by incorporating automated validation systems. Machine learning models can assess the compliance of production processes with specified standards, ensuring that validated processes align with quality requirements before release.

In conclusion, the integration of data science into the Chemical Process Design activity of Manufacturing Process Planning offers a data-driven approach to defining, optimizing, and validating production processes. Leveraging historical data, optimization algorithms, and automation, data science enhances the precision, efficiency, and quality of chemical manufacturing processes. This data-centric approach aligns with the broader objectives of manufacturing planning, fostering continuous improvement and informed decision-making (Braun et al., 2020; Duever, 2019; Mowbray et al., 2022; Qin & Dong, 2020).

4.2.1.12 Mitigation Strategies for Challenges in Adoption of Data Science

Table 15 outlines the integration of data science in the various facets of the Manufacturing Process Planning function, elucidating how each sub-process benefits from specific data science use cases. These applications are strategically aligned with business agility goals, offering insights into how data-driven methodologies can contribute to improving decision-making, fostering dynamic processes, and enhancing overall behavioral and situational awareness within the manufacturing domain. The integration of data science in the Manufacturing Process Planning function brings forth a plethora of benefits, from predictive modeling and AI-driven simulations to optimization of processes and enhanced decision-making.

Table 15 Data Science Use Cases for the various process in Manufacturing Process Planning function. Source : Author

Process	**Data Science Use Cases**	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Manufacturing Configuration Management	- Predictive modeling for Manufacturing Architecture optimization - Data-driven	- Create Dynamic Processes for Fast Execution- Improve	- Lack of skilled workforce - Data quality and availability	- Inadequate expertise in predictive modeling- Inaccurate or incomplete	- Provide specialized training in predictive modeling- Implement

Table 15 Data Science Use Cases for the various process in Manufacturing Process Planning function. Source : Author					
Process	**Data Science Use Cases**	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
	logistics planning	Behavioral Awareness	- Integration with existing systems	logistics data- Compatibility issues with existing systems	rigorous data quality checks- Collaborate with IT for seamless integration
Manufacturing Assembly Process Planning	- Predictive modeling for optimal assembly processes - resource optimization through machine learning	- Enable Augmented Decision Making- Create Dynamic Processes for Fast Execution- Improve Behavioral Awareness	- Lack of skilled workforce - Data quality and availability - Integration with existing systems	- Inadequate expertise in predictive modeling- Inaccurate or incomplete resource data- Compatibility issues with existing systems	- Provide specialized training in predictive modeling- Implement rigorous data quality checks- Collaborate with IT for seamless integration
Part Fabrication Planning and CNC Programme Management	- AI-based tool selection and machining program optimization - Simulation	- Enable Augmented Decision Making- Create Dynamic	- Lack of skilled workforce- Data quality and availability-	- Inadequate expertise in AI for tool selection and program optimization-	- Provide specialized training in AI-based tool selection-

Table 15 Data Science Use Cases for the various process in Manufacturing Process Planning function. Source : Author

Process	**Data Science Use Cases**	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
	and validation of CNC programs	Processes for Fast Execution- Improve Behavioral Awareness	Integration with existing systems	Inaccurate or incomplete machining data- Compatibility issues with existing systems	Implement rigorous data quality checks- Collaborate with IT for seamless integration
Part Inspection & Metrology Planning	- AI-driven inspection plan optimization- Predictive maintenance for inspection equipment	- Enable Augmented Decision Making- Create Dynamic Processes for Fast Execution- Improve Behavioral Awareness	- Lack of skilled workforce- Data quality and availability- Integration with existing systems	- Inadequate expertise in AI for inspection plan optimization- Inaccurate or incomplete inspection data- Compatibility issues with existing systems	- Provide specialized training in AI for inspection planning- Implement rigorous data quality checks- Collaborate with IT for seamless integration
Virtual Machine for CNC Program Validation	- Virtual simulation and Validation of CNC	- Enable Augmented Decision Making-	- Lack of skilled workforce- Data	- Inadequate expertise in AI for virtual simulation-	- Provide specialized training in AI for

Table 15 Data Science Use Cases for the various process in Manufacturing Process Planning function. Source : Author					
Process	**Data Science Use Cases**	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
	programs using AI-driven models	Create Dynamic Processes for Fast Execution-Improve Behavioral Awareness	quality and availability-Integration with existing systems	Inaccurate or incomplete simulation data-Compatibility issues with existing systems	virtual simulation-Implement rigorous data quality checks-Collaborate with IT for seamless integration
Production Quality and Inspection Planning	- Predictive modeling for quality control and inspection planning	- Enable Augmented Decision Making-Create Dynamic Processes for Fast Execution-Improve Behavioral Awareness	- Lack of skilled workforce-Data quality and availability-Integration with existing systems	- Inadequate expertise in predictive modeling-Inaccurate or incomplete quality data-Compatibility issues with existing systems	- Provide specialized training in predictive modeling -Implement rigorous data quality checks - Collaborate with IT for seamless integration

Table 15 Data Science Use Cases for the various process in Manufacturing Process Planning function. Source : Author					
Process	**Data Science Use Cases**	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Robotics Planning and Simulation	- AI-driven path planning and optimization for robots	- Enable Augmented Decision Making- Create Dynamic Processes for Fast Execution- Improve Behavioral Awareness	- Lack of skilled workforce- Data quality and availability- Integration with existing systems	- Inadequate expertise in AI for robotic path planning- Inaccurate or incomplete robotics data- Compatibility issues with existing systems	- Provide specialized training in AI for robotics planning- Implement rigorous data quality checks- Collaborate with IT for seamless integration
Formulated Product Quality Control [Lab Info Mgt Sys]	- Predictive analytics for resource planning and quality control optimization	- Enable Augmented Decision Making- Create Dynamic Processes for Fast Execution- Improve Behavioral Awareness	- Lack of skilled workforce- Data quality and availability- Integration with existing systems	- Inadequate expertise in predictive analytics- Inaccurate or incomplete resource planning data- Compatibility issues with	- Provide specialized training in predictive analytics- Implement rigorous data quality checks- Collaborate with IT for

Table 15 Data Science Use Cases for the various process in Manufacturing Process Planning function. Source : Author					
Process	**Data Science Use Cases**	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
				existing systems	seamless integration
Production Process Concept & Design	- Predictive modeling for optimal production processes	- Enable Augmented Decision Making- Create Dynamic Processes for Fast Execution- Improve Behavioral Awareness	- Lack of skilled workforce- Data quality and availability- Integration with existing systems	- Inadequate expertise in predictive modeling- Inaccurate or incomplete production process data- Compatibility issues with existing systems	- Provide specialized training in predictive modeling- Implement rigorous data quality checks- Collaborate with IT for seamless integration
Manufacturing Concept Planning	- AI-driven analysis for production technology and cost optimization	- Enable Augmented Decision Making- Create Dynamic Processes for Fast	- Lack of skilled workforce- Data quality and availability- Integration with	- Inadequate expertise in AI for production technology analysis- Inaccurate or incomplete	- Provide specialized training in AI for production technology analysis- Implement

Table 15 Data Science Use Cases for the various process in Manufacturing Process Planning function. Source : Author					
Process	**Data Science Use Cases**	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
		Execution-Improve Behavioral Awareness	existing systems	cost data-Compatibility issues with existing systems	rigorous data quality checks-Collaborate with IT for seamless integration
Chemical Process Design	- Predictive modeling for optimal chemical production processes	- Enable Augmented Decision Making-Create Dynamic Processes for Fast Execution-Improve Behavioral Awareness	- Lack of skilled workforce-Data quality and availability-Integration with existing systems	- Inadequate expertise in predictive modeling-Inaccurate or incomplete chemical process data-Compatibility issues with existing systems	- Provide specialized training in predictive modeling-Implement rigorous data quality checks-Collaborate with IT for seamless integration

The detailed table 15, provides a comprehensive overview of how data science use cases align with business agility goals, tackling challenges and mitigating risks through specialized training, rigorous data quality checks, and collaborative efforts with IT for seamless integration. This synergy between data science and manufacturing process planning sets the stage for a more agile, efficient, and responsive manufacturing ecosystem.

Data science applications across Manufacturing Process Planning are diverse, addressing challenges, improving decision-making, and enhancing the agility of the overall manufacturing lifecycle. From predictive modeling to data science - driven simulations, leveraging these technologies can significantly optimize processes, increase efficiency, and contribute to achieving business agility goals in manufacturing. Training, data quality checks, and collaboration with IT play a crucial role in mitigating challenges and ensuring successful integration of data science in each sub-process.

4.2.2 Mitigation Strategies for Challenges in Adoption of Data Science in Manufacturing Resources Planning

In the context of Manufacturing Planning, the sub-function of Manufacturing Resources involves critical activities such as Manufacturing Resources Management, Plant Configuration Management, and Tooling and Fixture Design. This section explores the integration of data science into these activities shown in *Figure 131* to enhance efficiency, decision-making, and resource optimization.

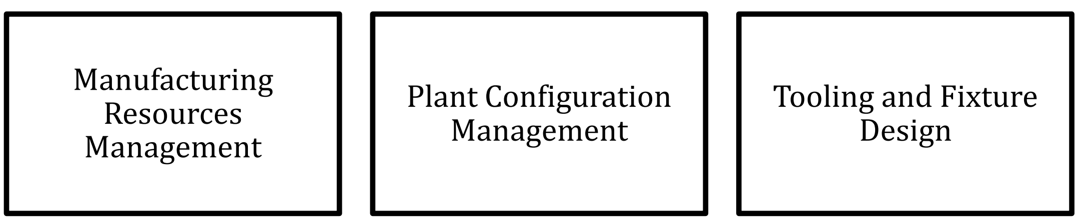

Figure 132 Typical Manufacturing Resources Planning Department Functions. Source:Author

4.2.2.1 Manufacturing Resources Management

In the domain of Manufacturing Planning, specifically within the Manufacturing Resources Planning function, the integration of data science into the Manufacturing Resources Management activity brings forth opportunities for optimization and efficiency. This section explores how data science can be applied to activities shown in *Figure 133***,** involving the definition of manufacturing resources, management of plant object standards, handling of manufacturing raw materials, maintenance of fixture and tooling libraries, and management of process and operation standards.

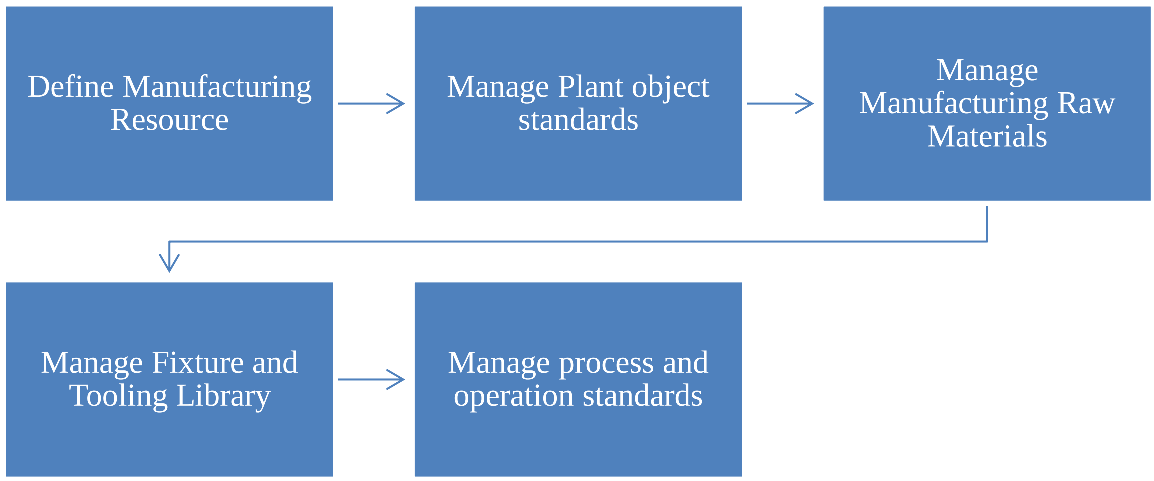

Figure 134 Typical Manufacturing Resources Management Process Flow. Source: Author

Data science plays a pivotal role in defining manufacturing resources by analyzing historical data and contextual information. Machine learning algorithms can identify patterns and predict optimal resource configurations, ensuring that manufacturing resources are tailored to specific requirements, thereby enhancing the overall planning process.

Managing plant object standards is streamlined through data-driven approaches. Predictive analytics models can assess the performance of different plant objects based on historical data, suggesting standards that optimize efficiency, reduce costs, and improve overall manufacturing resource utilization.

For the management of manufacturing raw materials, data science enables predictive inventory management. Machine learning models can analyze consumption patterns, supplier behavior, and market trends to predict raw material demands accurately. This ensures optimal inventory levels, preventing shortages or excesses.

Fixture and tooling libraries benefit from data science through automated maintenance and optimization. Algorithms can analyze historical usage data, recommending optimal fixture and tooling configurations to minimize downtime and improve production efficiency.

Data science contributes to the management of process and operation standards by automating the analysis of historical performance data. Machine learning models can identify correlations between different standards and operational outcomes, optimizing standards to improve overall manufacturing process efficiency.

In conclusion, the integration of data science into the Manufacturing Resources Management activity within Manufacturing Planning enhances the definition and utilization of resources. By leveraging machine learning algorithms and predictive analytics, organizations can optimize plant object standards, manage raw materials efficiently, automate fixture and tooling library maintenance, and improve process and operation standards. This data-centric approach contributes to more informed decision-making, increased efficiency, and enhanced overall performance in the manufacturing planning process (Kenett et al., 2018; Qin & Dong, 2020; Sajid et al., 2021; Vazan et al., 2017; Wang et al., 2014).

4.2.2.2 Plant Configuration Management

Within the domain of Manufacturing Planning, the activity of Plant Configuration Management in the Manufacturing Resources Planning sub-function involves various critical tasks shown in figure 75 related to managing the hierarchy and structural architecture of plans, handling building and surroundings information, importing and managing 3D scans, handling plant bills of equipment, managing plant evolutions, overseeing the plant digital twin, and validating and releasing plant configurations.

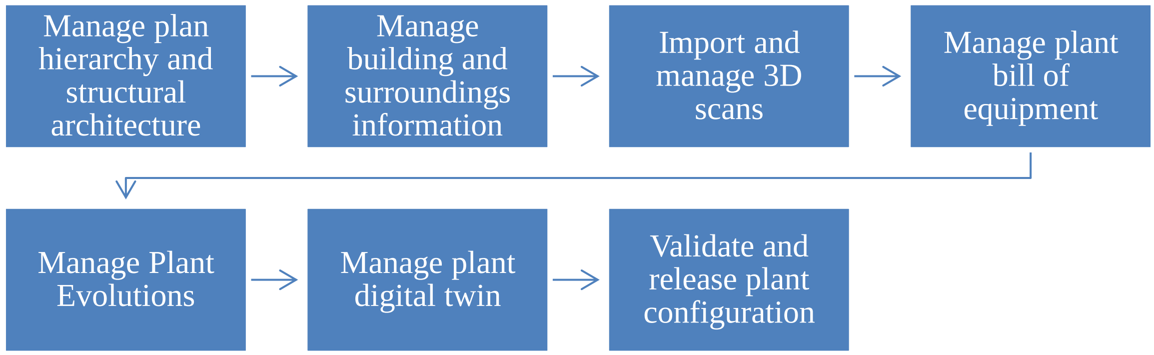

Figure 135 Typical Plant Configuration Management Process Flow. Source: Author

Data science contributes significantly to the management of plan hierarchy and structural architecture. Through machine learning algorithms, historical data on plan configurations, structural designs, and their performance can be analyzed to optimize the hierarchy and architecture of manufacturing plans, ensuring efficiency and effectiveness.

Managing building and surroundings information benefits from data science-driven analysis. Predictive models can assess environmental data, historical performance metrics, and other relevant factors to optimize building and surroundings information, contributing to a more informed decision-making process.

Importing and managing 3D scans is streamlined through data science techniques. Computer vision algorithms can analyze 3D scan data, extract valuable information, and assist in the integration of 3D scans into the plant configuration. This ensures accuracy and completeness in utilizing 3D scans for configuration purposes.

The management of plant bills of equipment is enhanced by data science-driven automation. Natural Language Processing (NLP) algorithms can process textual information in bills of equipment, extract relevant details, and automate the management process, improving accuracy and efficiency.

Plant evolutions are optimized through data-driven analysis of historical evolution data. Machine learning models can predict potential evolution paths based on past data, enabling proactive planning, and ensuring that evolutions align with strategic goals.

Managing the plant digital twin involves leveraging data science for continuous improvement. By analyzing real-time and historical data from the digital twin, organizations can identify areas for enhancement, optimize performance, and ensure that the digital twin remains an accurate representation of the physical plant.

Validation and release of plant configuration are improved through data-driven quality assurance. Predictive analytics models can assess the completeness and accuracy of plant configurations, flagging potential issues before release and ensuring that configurations meet specified standards.

In summary, the integration of data science into Plant Configuration Management activities within the Manufacturing Resources Planning sub-function enhances various aspects of manufacturing planning. From optimizing plan hierarchy and incorporating 3D scans to automating bill of equipment management and ensuring the accuracy of the digital twin, data science contributes to informed decision-making and efficient processes throughout the plant configuration lifecycle (Agard & Cunha, 2007; Gao et al., 2021; Kong et al., 2021; Layer et al., 2023; Neves et al., 2014; Zipper et al., 2018).

4.2.2.3 Tooling and Fixture Design

Within the Manufacturing Planning function, the Tooling and Fixture Design activity within Manufacturing Resources Planning involves crucial tasks shown in *Figure 136*, such as developing resource documentation, fixture design, tool design, testing and simulating tool and fixture movements, integrating designs with machine specifications, and validating and releasing both fixture and tool designs. This section explores how data science can enhance each of these activities.

Data science contributes to the development of resource documentation by automating the extraction of relevant information from various sources. Natural Language Processing (NLP) algorithms can analyze textual data to compile comprehensive and accurate resource documentation, reducing manual efforts and ensuring consistency.

In fixture design, data science aids in the optimization of the design process. Machine learning algorithms can analyze historical fixture design data, considering factors such as material properties, usage patterns, and performance metrics to suggest efficient and effective fixture designs.

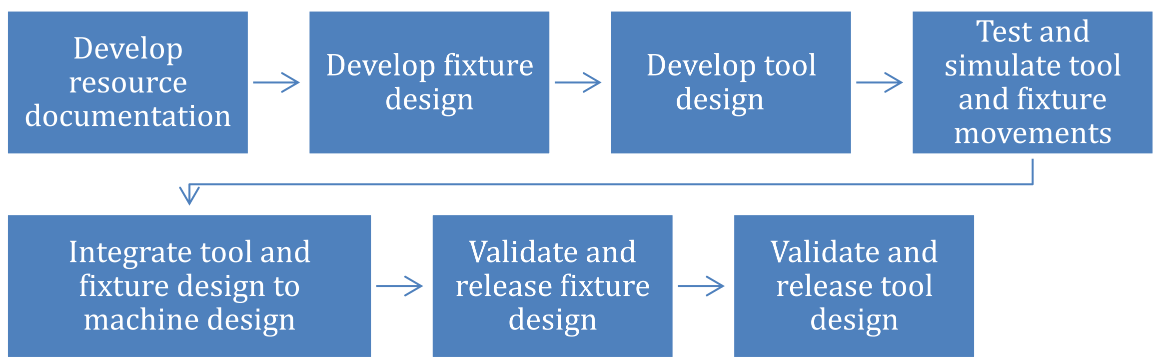

Figure 137 Typical Tooling and Fixture Design Process Flow. Source: Author

Similarly, data science plays a pivotal role in tool design by automating aspects of the process. Predictive modeling can assess the performance of different tool designs based on historical data, enabling the identification of optimal tool configurations that align with specific manufacturing requirements.

Testing and simulating tool and fixture movements benefit from data-driven simulations. Advanced simulations using machine learning can predict and analyze the movements, interactions, and potential issues related to tools and fixtures, allowing for more accurate assessments before physical implementation.

Integrating tool and fixture design with machine specifications is streamlined through data science. By utilizing compatibility algorithms and historical integration data, organizations can ensure seamless integration, reducing the likelihood of conflicts and inefficiencies in the manufacturing process.

Validation and release of fixture and tool designs are enhanced by data-driven quality assurance processes. Predictive analytics models can assess the compliance of designs with quality standards, allowing for automated validation and ensuring that only designs meeting predefined criteria are released for production.

In summary, the integration of data science into the Tooling and Fixture Design activity of Manufacturing Resources Planning optimizes resource documentation, enhances fixture and tool design processes, enables accurate simulations, facilitates smooth integration with machine specifications, and automates the validation and release processes. This data-centric approach contributes to improved efficiency, reliability, and quality assurance in the manufacturing planning domain (Cecil, 2002; Davé & Ball, 2013; Luo et al., 2021; Wang et al., 1993).

4.2.2.4 Mitigation Strategies for Challenges in Adoption of Data Science

Table 16 maps the Data Science use cases to the Manufacturing Resources Planning processes, aligning them with business agility goals, and addressing associated challenges and risks.

Table 16 Data Science Use Cases for the various process in Manufacturing Resources Planning function. Source : Author

Process	Data Science Use Cases	Business Agility Goals	Challenges	Risk	Mitigation Strategies
Manufacturing Resources Management	- Predictive modeling for resource optimization	- Enable Augmented Decision Making- Create Dynamic Resources for Fast Execution	- Lack of skilled workforce- Data quality and availability- Integration with existing systems	- Inadequate expertise in predictive modeling- Inaccurate or incomplete resource data- Compatibility issues with existing systems	- Provide specialized training in predictive modeling- Implement rigorous data quality checks- Collaborate with IT for seamless integration
Plant Configuration Management	- AI-based plant layout optimization	- Enable Augmented Decision Making- Create Dynamic Resources for Fast Execution	- Lack of skilled workforce- Data quality and availability- Integration with existing systems	- Inadequate expertise in AI for plant layout optimization- Inaccurate or incomplete plant configuration data- Compatibility issues with	- Provide specialized training in AI for plant layout optimization- Implement rigorous data quality checks- Collaborate with IT for

Table 16 Data Science Use Cases for the various process in Manufacturing Resources Planning function. Source : Author					
Process	**Data Science Use Cases**	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
				existing systems	seamless integration
Tooling and Fixture Design	- AI-driven design automation for tooling and fixtures	- Enable Augmented Decision Making- Create Dynamic Resources for Fast Execution	- Lack of skilled workforce- Data quality and availability- Integration with existing systems	- Inadequate expertise in AI for design automation- Inaccurate or incomplete tooling and fixture data- Compatibility issues with existing systems	- Provide specialized training in AI for design automation- Implement rigorous data quality checks- Collaborate with IT for seamless integration

Manufacturing Resources Management: In this process, AI-driven predictive modeling optimizes resource allocation, aligning with the goal of creating dynamic resources for fast execution. It enhances decision-making by providing insights into resource availability and requirements. Challenges such as a lack of skilled workforce and data quality issues are mitigated through specialized training programs and rigorous data quality checks. Collaborative efforts with IT ensure seamless integration.

Plant Configuration Management: AI is leveraged for plant layout optimization, contributing to augmented decision-making, and creating dynamic resources for fast execution. The goal is to efficiently plan and configure manufacturing plants based on real-time data. Challenges related to skilled workforce and data quality are addressed through specialized training and robust data quality checks, ensuring accurate plant configuration.

Tooling and Fixture Design: AI-driven design automation in tooling and fixture design streamlines processes, enabling augmented decision-making and creating dynamic resources for fast execution. This ensures efficient and optimized designs based on current manufacturing needs. Challenges related to skilled workforce and data quality are mitigated through specialized training programs and rigorous data quality checks. Collaboration with IT is key to ensuring the integration of AI in the design automation process.

In summary, the table provides a comprehensive overview of AI use cases in Manufacturing Resources Planning, aligning them with specific business agility goals. Challenges related to a lack of skilled workforce, data quality, and integration issues are identified, and mitigation strategies such as training programs, data quality checks, and collaboration with IT are proposed. This approach ensures that the implementation of data science in Manufacturing Resources Planning not only addresses specific business goals but also navigates potential challenges to achieve a more agile and efficient manufacturing ecosystem.

4.2.3 Mitigation Strategies for Challenges in Adoption of Data Science in Production Simulation

The Production Simulation function, within the broader scope of Supply Chain Collaboration and Material Management, encompasses critical sub-functions:

Manufacturing Process Simulation, Logistics Planning & Production Flow Simulation, and Dimensional Planning and Validation (DPV). This section explores how data science can be strategically applied to enhance these sub-functions shown in *Figure 138*, fostering improved behavioral awareness, situational awareness, inclusive decision-making, augmented decision-making, and dynamic processes and resources for fast execution.

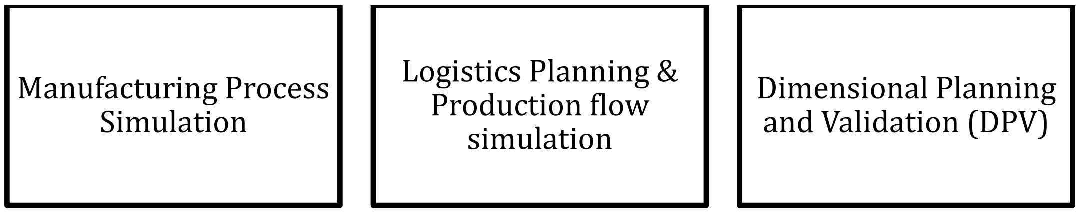

Figure 139 Typical Sub Function in Production Simulation Function. Source: Author

4.2.3.1 Manufacturing Process Simulation

Within the realm of manufacturing operations, the function responsible for "Manufacturing Process Simulation" plays a crucial role in ensuring efficiency, safety, and optimal performance. This section explores the diverse activities shown in *Figure 140* encompassed by this function, including checking assemble ability and reachability, human ergonomics studies, refining human-robot collaboration, robotic studies, workstation layout refinement, line, and conveyor setup refinement, defining process simulation models, and executing simulations with result analysis.

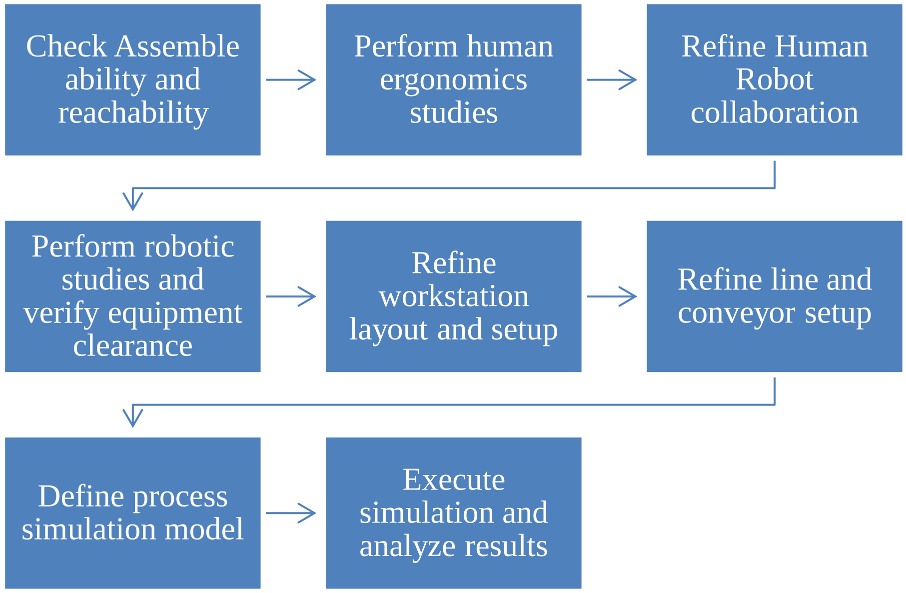

Figure 141 Typical Manufacturing Process Simulation Process Flow. Source: Author

The function of Manufacturing Process Simulation plays a pivotal role in ensuring the efficiency and viability of manufacturing operations. This section delves into the various activities encompassed by this function and explores how data science can be applied to improve behavioral awareness, situational awareness, enable inclusive decision-making, enable augmented decision-making, and create dynamic processes and resources for fast execution.

Check Assemble-ability and Reachability: This involves evaluating the feasibility of assembling components and assessing the reachability of critical elements in the manufacturing process. Data science can assist by analyzing historical assembly data, identifying potential bottlenecks, and optimizing assembly sequences to enhance efficiency.

Perform Human Ergonomics Studies: Human ergonomics studies focus on optimizing the interaction between workers and their environment. Data science can contribute by analyzing ergonomic data, predicting potential discomfort points, and recommending ergonomic adjustments to improve worker well-being and productivity.

Refine Human-Robot Collaboration: This activity involves enhancing collaboration between human workers and robots on the manufacturing floor. Data science can contribute by analyzing collaboration data, identifying areas for improvement, and optimizing human-robot interaction to maximize efficiency and safety.

Perform Robotic Studies and Verify Equipment Clearance: Robotic studies involve analyzing the movement and performance of robots in the manufacturing process. Data science can verify equipment clearance by simulating robot movements, identifying potential collisions, and optimizing robotic paths to ensure safe and efficient operations.

Refine Workstation Layout and Setup: Optimizing workstation layout and setup involves arranging workstations for optimal efficiency. Data science can assist by analyzing layout data, predicting workflow patterns, and recommending adjustments to streamline the manufacturing process.

Refine Line and Conveyor Setup: This activity focuses on optimizing the setup of production lines and conveyor systems. Data science can analyze production data, predict material flow patterns, and optimize line and conveyor configurations for increased throughput and efficiency.

Define Process Simulation Model: The creation of a process simulation model involves defining the parameters and variables for the simulation. Data science contributes by analyzing historical process data, identifying key factors, and creating simulation models that accurately represent the manufacturing process.

Execute Simulation and Analyze Results: The final step involves running the simulation and analyzing the results to assess the performance of the manufacturing process. Data science can aid in result analysis by comparing simulated and actual data, identifying discrepancies, and providing insights for process improvement.

In summary, the function of Manufacturing Process Simulation involves a series of activities aimed at optimizing various aspects of the manufacturing process. Data science emerges as a powerful tool to improve behavioral awareness, situational awareness, decision-making inclusivity, and augmentation, as well as to create dynamic processes and resources for fast execution. The application of data science in this function contributes to enhanced efficiency, adaptability, and overall agility in manufacturing operations (Flath & Stein, 2018; Giess & Culley, 2003; Jain et al., 2017; Kibira et al., 2015; Qin & Dong, 2020; Shao et al., 2014; Vazan et al., 2017).

4.2.3.2 Logistics Planning & Production flow Simulation.

The Logistics Planning & Production Flow Simulation function within the broader context of Supply Chain Collaboration and Material Management is instrumental in optimizing material flow, container logistics, and overall production efficiency. This section explores the various activities shown in *Figure 142*, performed by this function and delves into how data science can be employed to enhance business agility and decision-making.

Define Material Provisioning Strategy: This activity involves strategizing and defining how materials will be provisioned throughout the supply chain. Data science contributes by analyzing historical provisioning data, market trends, and demand forecasts. Machine learning models can optimize provisioning strategies, ensuring that materials are available when and where they are needed.

Define Container Types and Sizes: In this activity, the function determines the types and sizes of containers suitable for efficient material transportation. Data science plays a role in analyzing material characteristics, transportation routes, and historical logistics data. Optimization algorithms can then recommend container types and sizes that minimize costs and maximize efficiency.

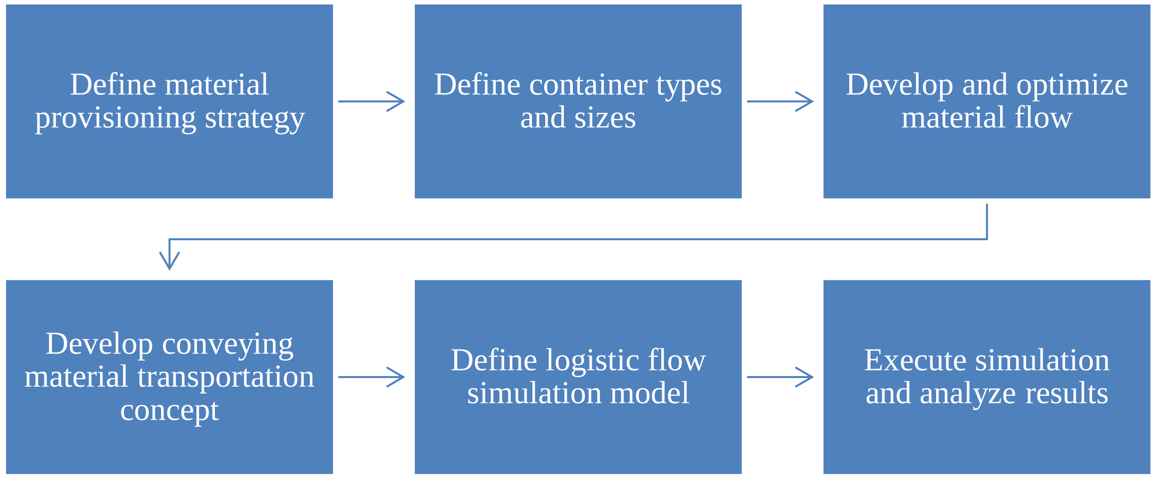

Figure 143 Typical Logistics Planning & Production flow simulation Process Flow. Source:Author

Develop and Optimize Material Flow: This activity focuses on designing and optimizing the flow of materials within the supply chain. Data science aids this process by analyzing historical material flow data, identifying bottlenecks, and optimizing routes. Predictive modeling can anticipate future flow patterns, enabling proactive adjustments for improved efficiency.

Develop Conveying Material Transportation Concept: Creating a transportation concept for conveying materials involves selecting the most suitable methods for material movement. Data science contributes by analyzing transportation costs, environmental impacts, and historical transportation data. Machine learning models can recommend transportation concepts that align with cost-effectiveness and sustainability goals.

Define Logistic Flow Simulation Model: This activity involves creating a simulation model to represent the logistics flow within the supply chain. Data science-driven simulation models use historical data to mimic real-world scenarios, allowing for the testing of various strategies and identifying potential improvements in the logistics flow.

Execute Simulation and Analyze Results: Executing the logistic flow simulation and analyzing results is a crucial step in understanding the performance of the proposed strategies. Data science facilitates this by processing simulation data and providing insights into the effectiveness of different logistic scenarios. Analytics tools can identify trends, inefficiencies, and opportunities for optimization.

In summary, the Logistics Planning & Production Flow Simulation function is pivotal in orchestrating efficient material flow and logistics within the supply chain. Leveraging data science enhances decision-making, augments operational processes, and fosters agility in response to dynamic conditions. The integration of AI tools improves behavioral and situational awareness, enables inclusive and augmented decision-making, and creates dynamic processes and resources for fast and efficient execution within the logistics domain. This data-centric approach contributes to overall business agility and optimization in the realm of supply chain collaboration and material management (Jain et al., 2001; Kibira et al., 2015; Liu & Takakuwa, 2011; Moldagulova et al., 2020; Oka et al., 2002).

4.2.3.3 Dimensional Planning and Validation (DPV)

The Dimensional Planning and Validation (DPV) function within the broader operational framework is responsible for a set of critical activities aimed at ensuring precision and accuracy in dimensional aspects of production. These activities shown in *Figure 144*, encompass gathering specifications and tolerances, defining measurement routines, managing measurement equipment, processing measurement data, and generating comprehensive reports.

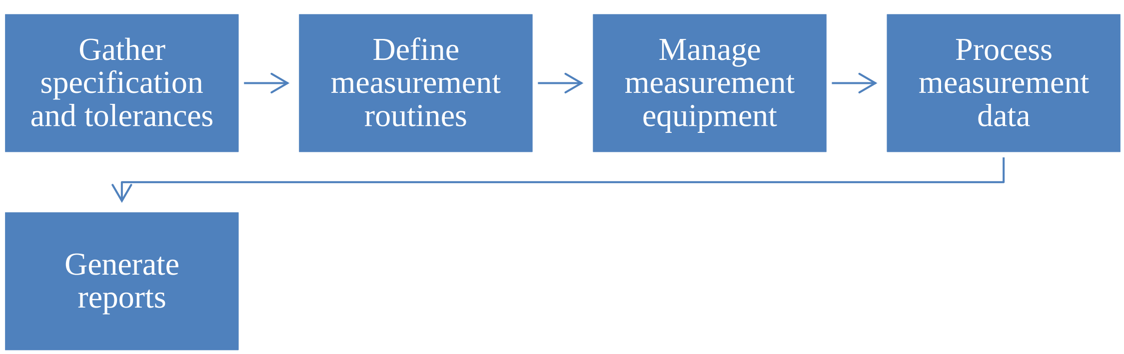

Figure 145 Typical Dimensional Planning and Validation (DPV) Process Flow. Source: Author

Gather Specification and Tolerances: This activity involves the collection of detailed specifications and tolerances relevant to the dimensional aspects of production. Data science can enhance this process by automating the extraction of specifications from diverse sources, ensuring accuracy, and maintaining a centralized repository for easy access and reference.

Define Measurement Routines: Defining measurement routines entails establishing systematic procedures for dimensional assessments. Data science can contribute by optimizing these routines through predictive modeling. Machine learning algorithms can analyze historical measurement data to suggest efficient and accurate measurement routines, adapting to evolving patterns and ensuring continuous improvement.

Manage Measurement Equipment: Efficient management of measurement equipment is crucial for dimensional accuracy. Data science aids in predictive maintenance, optimizing equipment performance by analyzing usage patterns and identifying potential issues before they lead to disruptions. This approach ensures that measurement equipment remains reliable and contributes to overall production efficiency.

Process Measurement Data: Processing measurement data involves analyzing collected data to derive meaningful insights. Data science enhances this process by implementing advanced analytics techniques. Machine learning algorithms can identify patterns, outliers, and trends in measurement data, facilitating a deeper understanding of dimensional variations and contributing to continuous improvement efforts.

Generate Reports: The generation of comprehensive reports is a pivotal aspect of the DPV function. Data science automates report generation by utilizing algorithms that process measurement data and present insights in a clear and actionable format. This ensures that stakeholders receive timely and accurate information, supporting informed decision-making.

In summary, the Dimensional Planning and Validation (DPV) function is a critical component of the operational framework, ensuring precision in dimensional aspects of production. Data science significantly enhances this function by optimizing measurement routines, managing equipment, processing data, and generating reports. Additionally, data science fosters business agility by improving behavioral awareness, situational awareness, enabling inclusive and augmented decision-making, and creating dynamic processes and resources for fast execution. This integration of data science not only ensures accuracy in dimensional planning but also contributes to the overall agility and efficiency of the production processes (Caballero et al., 2015; Mousa et al., 2015; Pacheco et al., 2014; Parham et al., 2016).

4.2.3.4 Mitigation Strategies for Challenges in Adoption of Data Science

This Section will attempt to construct a table mapping Data Science use cases to the Production Simulation processes, aligning them with business agility goals, and addressing associated challenges and risks.

Manufacturing Process Simulation: Data science is applied through predictive modeling for optimizing workstation layouts, enabling augmented decision-making, and creating dynamic processes for fast execution. Challenges such as a lack of skilled workforce and data quality issues are mitigated through specialized training and rigorous data quality checks. Collaborative efforts with IT ensure seamless integration, addressing compatibility issues. Table 17 summarizes the different data science use cases in this domain, associated challenges and risk along with the proposed mitigation strategies that can be taken by organizations.

Table 17 Data Science Use Cases for the various process in Production Simulation function - Manufacturing Process Simulation Sub Function. Source : Author

Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Predictive modeling for workstation layout optimization	- Improve Behavioral Awareness - Enable Augmented Decision Making	- Lack of skilled workforce - Data quality and availability - Integration with existing systems	- Inadequate expertise in predictive modeling - Inaccurate or incomplete data for simulation - Compatibility issues with existing systems	- Provide specialized training in predictive modeling- Implement rigorous data quality checks- Collaborate with IT for seamless integration
Machine learning for refining human-robot collaboration	- Improve Situational Awareness - Enable Augmented Decision Making	- Lack of skilled workforce - Integration with existing systems - Privacy and security concerns	- Inadequate expertise in machine learning - Integration challenges with existing systems - Data privacy risks	- Provide specialized training in machine learning techniques - Ensure compliance with data privacy regulations - Collaborate with IT for secure integration
Simulation-based process optimization	- Create Dynamic	- Data quality and availability - Scalability	- Inaccurate or incomplete data for simulation	- Implement rigorous data quality checks

Table 17 Data Science Use Cases for the various process in Production Simulation function - Manufacturing Process Simulation Sub Function. Source : Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
	Processes for Fast Execution	- Lack of standardization	- Scalability issues with large datasets - Lack of standardized simulation protocols	- Explore scalable data storage and processing solutions - Develop standardized simulation protocols

Logistics Planning & Production flow simulation: Optimization algorithms and predictive modeling are utilized for developing material flow and logistics planning, aligning with business agility goals. Challenges related to skilled workforce and data quality are mitigated through specialized training and rigorous data quality checks. Collaborative efforts with IT ensure seamless integration, addressing compatibility issues with existing systems. Table 18 summarizes the different data science use cases in this domain, associated challenges and risk along with the proposed mitigation strategies that can be taken by organizations.

Table 18 Data Science Use Cases for the various process in Logistics Planning & Production flow simulation - Manufacturing Process Simulation Sub Function. Source : Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
- Predictive modeling for	- Improve Behavioral Awareness-	- Lack of skilled workforce- Data quality and	- Inadequate expertise in predictive	- Provide specialized training in

Table 18 Data Science Use Cases for the various process in Logistics Planning & Production flow simulation - Manufacturing Process Simulation Sub Function. Source : Author

Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
optimizing material flow	Create Dynamic Processes for Fast Execution	availability- Integration with existing systems	modeling- Inaccurate or incomplete data for simulation- Compatibility issues with existing systems	predictive modeling- Implement rigorous data quality checks- Collaborate with IT for seamless integration
- Machine learning for optimizing logistic flow	- Improve Situational Awareness- Enable Augmented Decision Making	- Lack of skilled workforce- Integration with existing systems- Privacy and security concerns	- Inadequate expertise in machine learning- Integration challenges with existing systems- Data privacy risks	- Provide specialized training in machine learning techniques- Ensure compliance with data privacy regulations- Collaborate with IT for secure integration

Table 18 Data Science Use Cases for the various process in Logistics Planning & Production flow simulation - Manufacturing Process Simulation Sub Function. Source : Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
- Simulation-based logistics planning and optimization	- Enable Inclusive Decision Making- Create Dynamic Processes for Fast Execution	- Data quality and availability- Scalability- Lack of standardization	- Inaccurate or incomplete data for simulation- Scalability issues with large datasets- Lack of standardized simulation protocols	- Implement rigorous data quality checks- Explore scalable data storage and processing solutions- Develop standardized simulation protocols

Dimensional Planning and Validation (DPV): Machine learning is employed for processing and analyzing measurement data, facilitating augmented decision-making and dynamic processes. Table 19 summarizes the different data science use cases in this domain, associated challenges and risk along with the proposed mitigation strategies that can be taken by organizations.

Table 19 Data Science Use Cases for the various process in Production Simulation function - Dimensional Planning and Validation (DPV) Sub function. Source: Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Predictive analytics for measurement	Improve Behavioral Awareness-	Lack of skilled workforce- Integration with	Inadequate expertise in predictive	Provide specialized training in

Table 19 Data Science Use Cases for the various process in Production Simulation function - Dimensional Planning and Validation (DPV) Sub function. Source: Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
equipment maintenance	Enable Augmented Decision Making	existing systems-Scalability	analytics-Integration challenges with existing systems-Scalability issues with data volume	predictive analytics techniques-Collaborate with IT for seamless integration-Explore scalable data storage and processing solutions
Machine learning for identifying measurement anomalies	Improve Situational Awareness-Enable Augmented Decision Making	Data quality and availability-Privacy and security concerns- Lack of standardization	Inaccurate or incomplete data for analysis- Data privacy risks-Lack of standardized anomaly detection protocols	Implement rigorous data quality checks-Ensure compliance with data privacy regulations-Develop standardized anomaly detection protocols

Table 19 Data Science Use Cases for the various process in Production Simulation function - Dimensional Planning and Validation (DPV) Sub function. Source: Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Simulation-based dimensional planning and validation	Create Dynamic Processes for Fast Execution	Lack of skilled workforce- Data quality and availability- Integration with existing systems	Inadequate expertise in simulation techniques- Inaccurate or incomplete data for simulation- Compatibility issues with existing systems	Provide specialized training in simulation techniques- Implement rigorous data quality checks- Collaborate with IT for seamless integration

Challenges such as a lack of skilled workforce and data quality issues are addressed through specialized training and rigorous data quality checks. Collaborative efforts with IT ensure seamless integration, mitigating compatibility issues.

In summary, the table provides a comprehensive overview of how data science use cases in Production Simulation align with business agility goals and tackle associated challenges and risks. Through predictive modeling, machine learning, and optimization algorithms, organizations can enhance decision-making, foster dynamic processes, and address challenges to achieve a more agile manufacturing planning department.

4.2.4 Mitigation Strategies for Challenges in Adoption of Data Science in Specialized Manufacturing Process Planning

Within the context of specialized manufacturing process planning, this section explores various sub-functions critical to the manufacturing industry. The focus is on understanding the intricacies of each sub-function shown in *Figure 146* and how data science applications can enhance operational aspects, behavioral awareness, situational awareness, decision-making inclusivity, augmented decision-making, as well as the creation of dynamic processes and resources for fast execution.

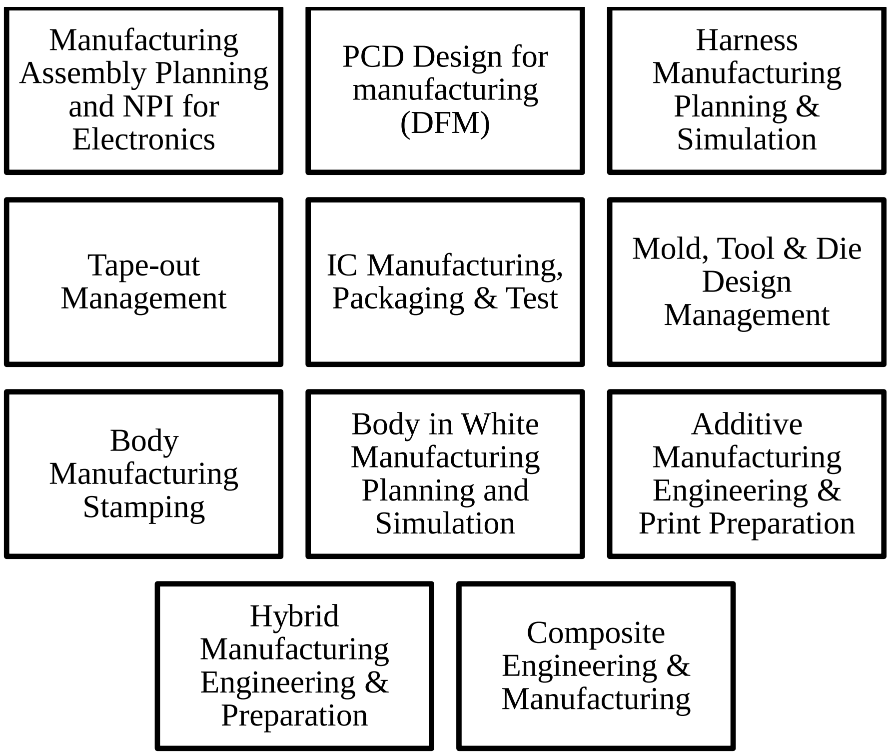

Figure 147 Typical Sub Functions Specialized Manufacturing Process Planning. Source: Author

4.2.4.1 Manufacturing Assembly Planning and NPI for Electronics

The Manufacturing Assembly Planning and New Product Introduction (NPI) function in the context of electronics encompasses a range of activities vital to the production and introduction of new electronic products. This section delves into key activities within this function shown in *Figure 148* and explores how data science can be instrumental in enhancing these processes.

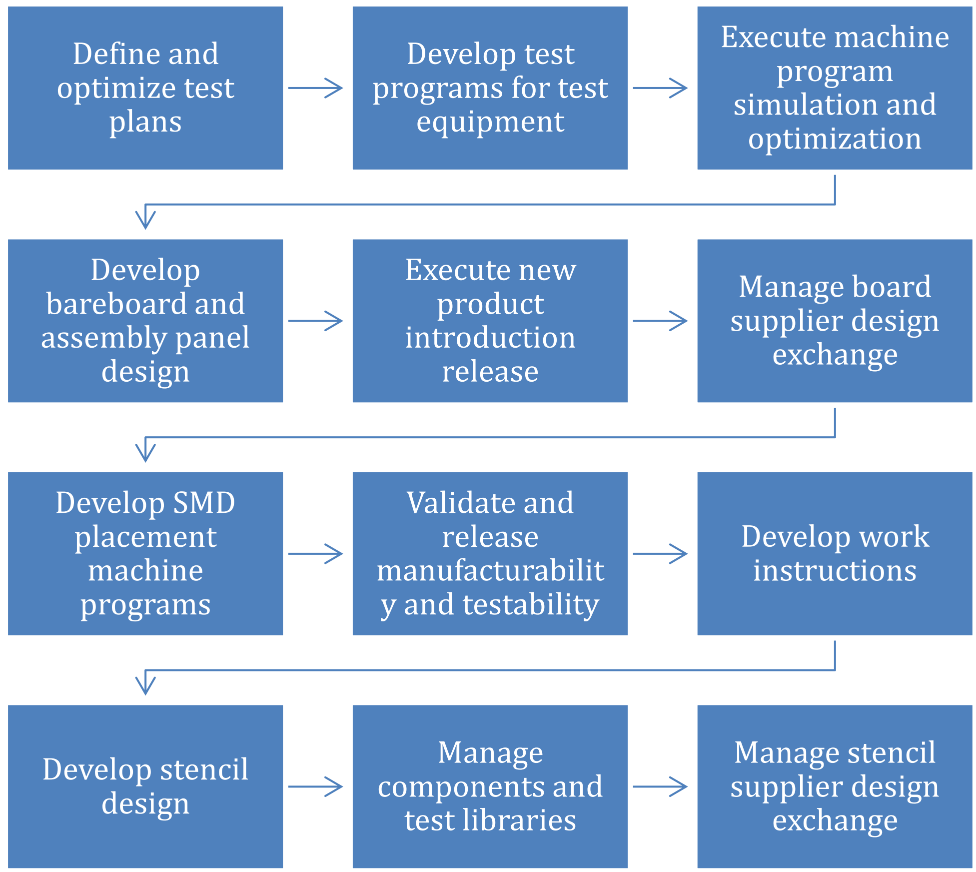

Figure 149 Typical Assembly Planning and NPI for Electronics Process Flow. Source: Author

Define and Optimize Test Plans: This activity involves defining comprehensive test plans to ensure the quality and functionality of electronic components. Data science can contribute by analyzing historical test data, identifying patterns, and optimizing test plans for efficiency and effectiveness.

Develop Test Programs for Test Equipment: Data science aids in developing test programs by analyzing equipment capabilities and historical performance data. Machine learning algorithms can optimize test programs, ensuring accurate and efficient testing of electronic components.

Execute Machine Program Simulation and Optimization: Simulating and optimizing machine programs is crucial for efficiency in electronic manufacturing. Data science, through simulation models, can predict machine behavior, identify bottlenecks, and optimize programs for enhanced production throughput.

Develop Bareboard and Assembly Panel Design: This activity involves designing the bareboard and assembly panels for electronic components. Data science, utilizing design optimization algorithms, can enhance the efficiency of these designs, ensuring optimal component placement and assembly.

Execute New Product Introduction Release: Data science contributes to the NPI release process by analyzing historical NPI data, predicting potential issues, and optimizing release strategies. This ensures a smoother transition from design to production for new electronic products.

Manage Board Supplier Design Exchange: Efficient exchange of design information with board suppliers is vital. Data science facilitates this process by automating data exchange, ensuring accuracy, and providing real-time insights into supplier collaboration.

Develop SMD Placement Machine Programs: Creating machine programs for Surface Mount Device (SMD) placement is critical for assembly. Data science optimizes these programs by analyzing historical placement data, identifying optimal configurations, and improving accuracy.

Validate and Release Manufacturability and Testability: Data science plays a key role in validating manufacturability and testability by analyzing design data and predicting potential manufacturing and testing issues. This proactive approach ensures smoother production and testing processes.

Develop Work Instructions: Creating detailed work instructions is essential for efficient manufacturing. Data science can automate the generation of work instructions by analyzing design data and historical manufacturing processes, ensuring accuracy and clarity.

Develop Stencil Design: Stencil design is critical for accurate component placement. Data science, through optimization algorithms, improves stencil designs by analyzing historical placement data and identifying optimal designs for specific components.

Manage Components and Test Libraries: Efficient management of component and test libraries is essential for streamlined processes. Data science automates library management, ensuring accurate information, and facilitating quick access to components and test data.

Manage Stencil Supplier Design Exchange: Exchange of stencil design information with suppliers is crucial. Data science automates this exchange process, ensuring consistency, accuracy, and real-time collaboration with stencil suppliers.

In summary, the Manufacturing Assembly Planning and NPI function for electronics involves a multifaceted set of activities crucial for efficient production and new product introduction. Leveraging data science in these processes enhances behavioral and situational awareness, promotes inclusive and augmented decision-making, and facilitates dynamic processes and resource allocation for fast and efficient execution within the electronics manufacturing domain (Doganaksoy & Hahn, 2014; Herrera et al., 2019; Kibira et al., 2015; Sajid et al., 2021; Vazan et al., 2017; Vodencarevic & Fett, 2015).

4.2.4.2 PCB Design for manufacturing (DFM)

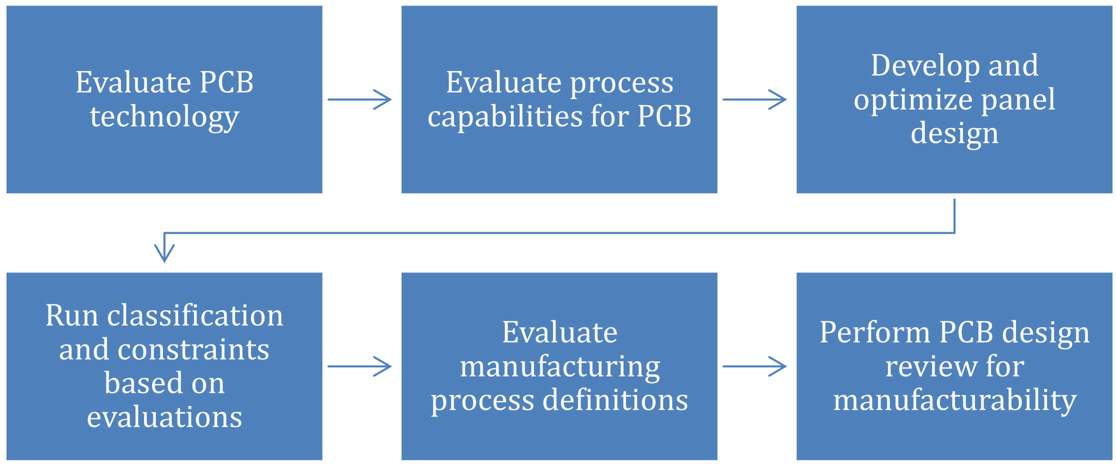

Figure 150 Typical PCB Design for manufacturing (DFM) Process Flow. Source : Author

The function responsible for "PCB Design for Manufacturing (DFM)" plays a crucial role in ensuring the manufacturability and efficiency of Printed Circuit Board (PCB) designs. This section explores the activities encompassed by this function as shown in *Figure 151* and delves into how data science can be strategically employed to enhance various aspects, fostering business agility.

Evaluate PCB Technology: This activity involves assessing the available PCB technologies in the market. Data science can facilitate this process by analyzing historical data on technology performance, identifying emerging trends, and predicting the potential impact of adopting specific technologies on design and manufacturing.

Evaluate Process Capabilities for PCB: The evaluation of process capabilities for PCB manufacturing requires a comprehensive analysis of the manufacturing processes. Data science can contribute by employing predictive modeling to assess the capabilities of different processes, enabling informed decisions on the most suitable manufacturing methods.

Develop and Optimize Panel Design: Developing and optimizing panel designs involves arranging PCBs on manufacturing panels for efficient production. Data science-driven algorithms can optimize panel layouts based on factors like size, shape, and material efficiency, ensuring resource utilization and reducing waste.

Run Classification and Constraints Based on Evaluations: Data science can automate the classification of PCB designs and apply constraints based on evaluations. Machine learning algorithms can analyze design characteristics and historical performance data to classify designs and enforce constraints, ensuring compliance with manufacturing standards.

Evaluate Manufacturing Process Definitions: This activity involves scrutinizing the definitions of manufacturing processes. Data science can aid in this by automating the analysis of process definitions, identifying potential bottlenecks, and recommending optimizations to streamline the manufacturing workflow.

Perform PCB Design Review for Manufacturability: Conducting PCB design reviews for manufacturability is crucial for identifying issues early in the design phase. Data science can contribute by developing automated review tools that analyze designs, predict potential manufacturing challenges, and provide actionable insights to design teams.

In summary, the PCB Design for Manufacturing (DFM) function involves critical activities ranging from technology evaluation to design optimization. Integrating data science enhances various facets, fostering business agility through improved behavioral and situational awareness, inclusive and augmented decision-making, and the creation of dynamic processes and resources for fast execution. This strategic use of data science ensures adaptability and efficiency within the broader context of Supply Chain Collaboration and Material Management (Bajaj et al., 2003; Ferrer et al., 2009; Hamulczuk & Isaksson, 2021; Phelan et al., 2014; Pitchumani, 2005).

4.2.4.3 Harness Manufacturing Planning & Simulation

The function responsible for "Harness Manufacturing Planning & Simulation" is integral to the efficient planning and execution of harness manufacturing processes. This section explores the key activities undertaken by this function as shown in *Figure 152*, namely defining production modules, generating bill of process, analyzing harnesses' cost, designing formboard, performing line balancing, and generating electronic work instructions.

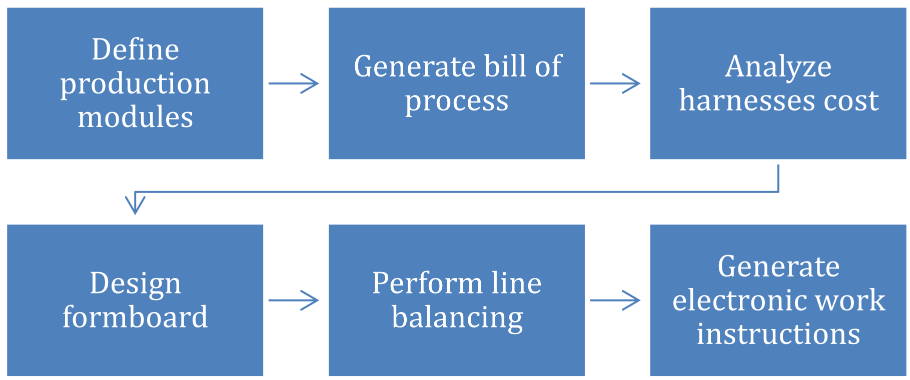

Figure 153 Typical Harness Manufacturing Planning & Simulation Process Flow. Source: Author

Define Production Modules: This activity involves breaking down the manufacturing process into distinct production modules. Each module is designed to address specific components or functionalities, facilitating a modular and organized approach to harness manufacturing.

Generate Bill of Process: The generation of a bill of process entails outlining the detailed steps and operations involved in manufacturing harnesses. This document serves as a comprehensive guide, ensuring consistency and accuracy in the manufacturing workflow.

Analyze Harness Costs: Cost analysis is crucial for optimizing manufacturing processes. Data science can be instrumental in this activity by employing cost modeling and predictive analytics to analyze historical data, predict future costs, and identify opportunities for cost reduction.

Design Formboard: The design of formboards involves creating layouts for arranging harness components during the manufacturing process. Data science can contribute by utilizing optimization algorithms to arrange components efficiently, considering factors such as spatial constraints and workflow efficiency.

Perform Line Balancing: Line balancing is the optimization of work distribution across manufacturing lines to minimize idle time and maximize efficiency. Data science can aid in this activity by employing algorithms that consider factors such as task duration, worker skills, and production goals to achieve optimal line balancing.

Generate Electronic Work Instructions: Electronic work instructions replace traditional paper-based instructions, providing a digital guide for workers on the manufacturing floor. Data science can streamline this process by incorporating Natural Language Processing (NLP) algorithms to convert technical documents into clear and concise electronic instructions.

In summary, the function responsible for "Harness Manufacturing Planning & Simulation" engages in crucial activities to optimize harness manufacturing. The integration of data science enhances these activities, contributing to cost analysis, efficient line balancing, and the generation of electronic work instructions. Furthermore, by leveraging data science, the function can achieve business agility goals, including improved behavioral and situational awareness, inclusive and augmented decision-making, and the creation of dynamic processes and resources for fast execution (Filz et al., 2020; Flath & Stein, 2018; Gao et al., 2014; Kibira et al., 2015; Krenczyk, 2012; Vazan et al., 2017).

4.2.4.4 Tape-out Management

The Tape-out Management function within the semiconductor industry encompasses crucial activities ranging from creating photolithography mask designs to managing mask design data, executing tape-out design checks, reviewing, and releasing tape-out designs, and managing the mask order process. The integration of data science in this function and its activities shown in *Figure 154***,** introduces opportunities for efficiency, accuracy, and improved business agility.

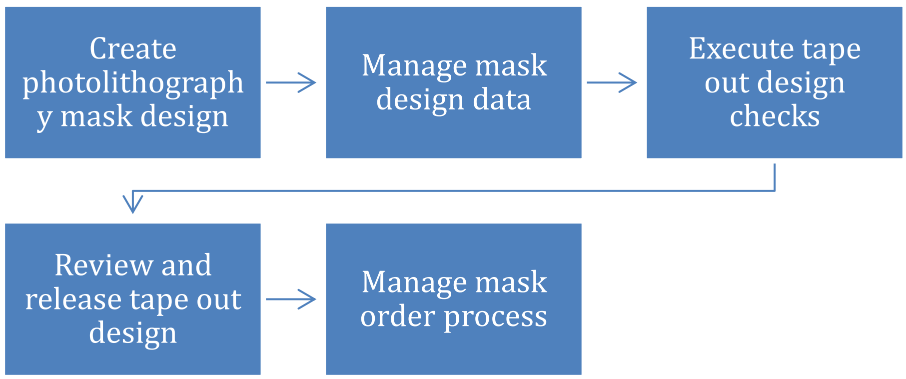

Figure 155 Typical Tape-out Management function Process Flow. Source: Author

Create Photolithography Mask Design: This activity involves generating precise photolithography mask designs critical for semiconductor manufacturing. Data science contributes by utilizing algorithms to optimize design parameters, ensuring accuracy and efficiency in the mask creation process.

Manage Mask Design Data: Data science aids in organizing and analyzing mask design data. Machine learning algorithms can enhance data management by automating data tagging, classification, and retrieval processes, leading to more efficient data handling.

Execute Tape Out Design Checks: Data science-driven design checks leverage algorithms to scrutinize tape-out designs for potential errors or deviations from specifications. This ensures the identification and rectification of issues before the manufacturing phase, reducing costly errors.

Review and Release Tape Out Design: Automated review processes, powered by data science, streamline the assessment of tape-out designs. Predictive models can evaluate design quality and adherence to specifications, facilitating faster and more informed decision-making during the review process.

Manage Mask Order Process: Data science contributes to optimizing the mask order process by analyzing historical order data and predicting future demand. This allows for efficient resource allocation, timely order processing, and improved overall process management.

Incorporating data science into Tape-out Management activities in the semiconductor industry introduces efficiencies in mask design, data management, design checks, review processes, and overall process optimization. Leveraging AI for business agility goals enhances behavioral and situational awareness, promotes inclusive and augmented decision-making, and enables dynamic processes and resource allocation. While challenges like a lack of skilled workforce and privacy concerns exist, strategic mitigation approaches can address these issues, ensuring successful adoption and integration of data science practices (Ackmann et al., 1994; Herrera et al., 2019; Leng et al., 2012; Qin & Dong, 2020; Rangan & Fulton, 1991; Vodencarevic & Fett, 2015).

4.2.4.5 IC Manufacturing, Packaging & Test

The function of Integrated Circuit (IC) Manufacturing, Packaging & Test is a critical component within the broader framework of semiconductor production. This multifaceted function encompasses several key activities as shown in *Figure 156*, including defining materials, defining fabrication technology, developing IC fabrication, and packaging processes, analyzing thermal behavior, developing IC test plans, and managing material and fabrication technology knowledge.

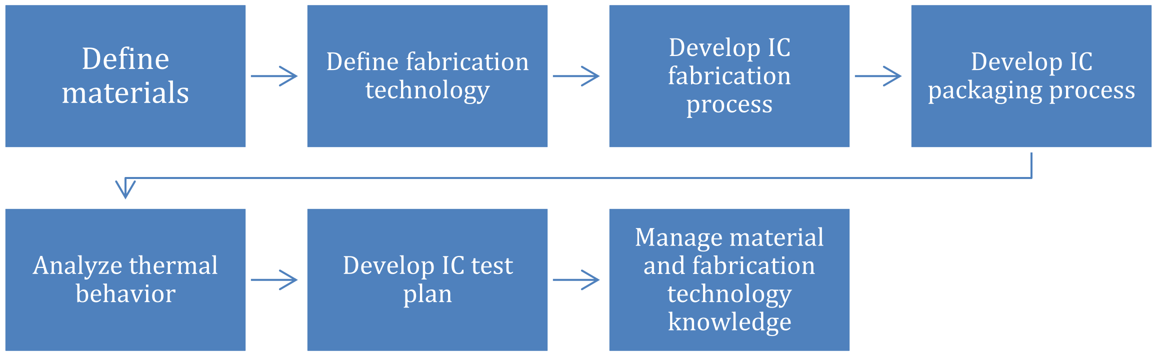

Figure 157 IC Manufacturing, Packaging & Test Process Flow. Source: Author

Define Materials: This activity involves specifying the materials used in the production of integrated circuits. Data science can contribute by analyzing material properties, historical performance data, and supplier information to optimize material selection, ensuring compatibility with fabrication processes and meeting performance requirements.

Define Fabrication Technology: Defining the fabrication technology is crucial for determining the manufacturing processes employed in IC production. Data science supports this activity by analyzing technological trends, historical process data, and industry benchmarks to inform decisions about the most suitable and efficient fabrication technologies.

Develop IC Fabrication Process: The development of IC fabrication processes involves creating detailed procedures for manufacturing integrated circuits. Data science can assist in optimizing these processes by analyzing historical production data, identifying bottlenecks, and recommending improvements for increased efficiency and yield.

Develop IC Packaging Process: Like fabrication, packaging processes require meticulous development. Data science contributes by analyzing packaging data, optimizing material usage, and predicting failure points, ensuring the reliability and performance of packaged integrated circuits.

Analyze Thermal Behavior: Analyzing the thermal behavior of integrated circuits is essential for preventing overheating and ensuring optimal performance. Data science techniques, such as thermal modeling and simulation, can be employed to predict and optimize thermal characteristics, contributing to the overall reliability of ICs.

Develop IC Test Plan: The development of a comprehensive test plan is vital for ensuring the functionality and quality of integrated circuits. Data science aids in developing effective test plans by analyzing historical test data, identifying critical test parameters, and optimizing testing procedures for enhanced product validation.

Manage Material and Fabrication Technology Knowledge: This activity involves systematically organizing and managing knowledge related to materials and fabrication technologies. Data science solutions, such as knowledge graphs and semantic analysis, can be employed to structure and retrieve information efficiently, fostering a more informed decision-making process.

In conclusion, the integration of data science into the activities of Integrated Circuit Manufacturing, Packaging & Test enhances various aspects of the semiconductor production process. From optimizing materials and fabrication processes to improving behavioral and situational awareness, data science contributes to business agility by fostering inclusive and augmented decision-making and creating dynamic processes and resources for fast execution within the integrated circuit production landscape (Doudkin & Inyutin, 2021; ElGabry et al., 2018; Kibira et al., 2015; Chen et al., 2006; Siddiqui et al., 2020; Stoyanov et al., 2019).

4.2.4.6 Mold, Tool & Die Design Management

Within the realm of material management, the "Mold, Tool & Die Design Management" function plays a crucial role in ensuring the effective design and simulation of molds and tools for manufacturing processes. This section delves into the activities encompassed by this function shown in *Figure 158*, including the review of part design, development of mold and tooling design, simulation of mold operation, and validation and release of mold designs. Additionally, the discussion will address how data science can enhance these activities.

Review Part Design: This activity involves a meticulous examination of the part design before mold and tooling development begins. Data science can contribute by automating the review process, utilizing algorithms to identify potential design issues, ensuring compatibility with manufacturing processes, and expediting the initial assessment.

Develop Mold Design: The development of mold design is a core aspect of this function. Data science can be instrumental in this activity by leveraging machine learning models to analyze historical mold designs, identify optimization opportunities, and provide insights for creating more efficient and effective mold designs.

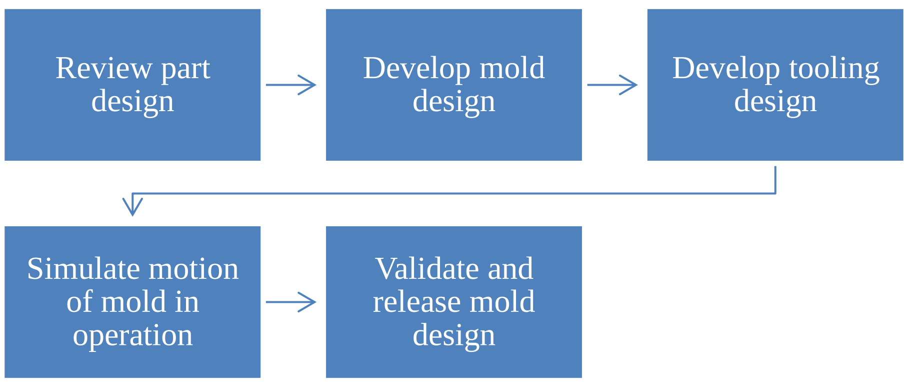

Figure 159 Typical Mold, Tool & Die Design Management Process Flow.
Source : Author

Develop Tooling Design: Like mold design, data science can enhance the development of tooling design. By analyzing historical tooling designs, predicting optimal tool configurations, and automating aspects of the design process, data science contributes to the creation of high-performance tooling.

Simulate Motion of Mold in Operation: Simulation of mold motion is crucial to identify potential issues and optimize the operation of the mold. Data science, particularly through the application of simulation models and algorithms, aids in accurately predicting the motion of molds during operation, ensuring efficiency, and minimizing errors.

Validate and Release Mold Design: This final activity involves thorough validation and subsequent release of the mold design for manufacturing. Data science can streamline this process by automating validation checks, utilizing predictive analytics to anticipate potential manufacturing challenges, and facilitating a more informed decision-making process for releasing the validated mold designs.

In summary, the "Mold, Tool & Die Design Management" function involves critical activities such as reviewing part design, developing mold and tooling designs, simulating mold operation, and validating and releasing designs. The integration of data science enhances these activities by automating processes, optimizing designs, and facilitating informed decision-making. Additionally, data science contributes to business agility by improving behavioral awareness, situational awareness, inclusive decision-making, augmented decision-making, and creating dynamic processes and resources for fast execution. This integration positions the function to adapt swiftly to changing conditions and contribute to the overall agility of the material management processes (Huang et al., 2009; Jong & Lai, 2011; Kozjek et al., 2019; Low & Lee, 2008; Nagahanumaiah et al., 2005).

4.2.4.7 Stamping Process in Body Manufacturing

The Stamping Process in Body Manufacturing plays a crucial role in shaping the components that form the structural foundation of an automobile. This section delves into the intricate activities performed by this function as shown in *Figure 160*, encompassing the development of press line layout, die station design, die structure and component design, binder and addendum modeling, formability analysis, die operation planning, die machining execution, and the validation and release of design results.

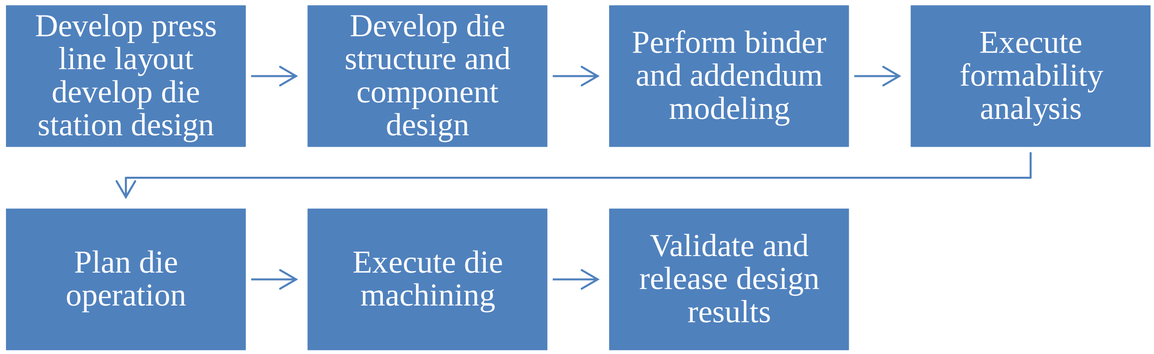

Figure 161 Typical Stamping Process in Body Manufacturing process Flow. Source: Author

Develop Press Line Layout: This activity involves designing the layout for the press line, determining the arrangement of presses and associated equipment. Data science contributes by analyzing historical production data and optimizing layouts for efficiency, minimizing downtime, and maximizing throughput.

Develop Die Station Design: Die station design focuses on creating the physical layout of the die stations. Data science can assist in optimizing the arrangement by analyzing factors such as material flow, station ergonomics, and historical performance data to enhance overall efficiency.

Develop Die Structure and Component Design: This activity involves creating the structural design of the die and its individual components. Data science applications, including generative design algorithms, can optimize designs based on performance criteria, material constraints, and historical design success data.

Perform Binder and Addendum Modeling: Binder and addendum modeling is crucial for determining the shape and structure of the die components. Data science aids in optimizing these models by analyzing historical formability data and material behavior, ensuring accurate and efficient forming processes.

Execute Formability Analysis: Formability analysis assesses how materials will behave under various forming conditions. Data science can enhance this process by simulating multiple scenarios, considering material properties and historical formability data to predict and optimize the formability of stamped components.

Plan Die Operation: Planning die operations involves scheduling and sequencing the manufacturing steps. Data science supports efficient planning by analyzing production data, machine availability, and historical operation times, facilitating optimized scheduling for faster production cycles.

Execute Die Machining: Die machining involves the actual production of dies based on the designed specifications. Data science contributes by optimizing machining processes, predicting tool wear, and ensuring precision through real-time monitoring and control.

Validate and Release Design Results: Validation of design results is critical before full-scale production. Data science applications, including machine learning models, can validate designs by comparing simulated results with historical production data, ensuring accuracy and reliability before releasing them for production.

In summary, the Stamping Process in Body Manufacturing encompasses a series of intricate activities vital for shaping automotive components. The integration of data science optimizes these activities, enhancing efficiency, accuracy, and overall business agility. By utilizing AI tools, the stamping process can achieve goals such as improved behavioral awareness, heightened situational awareness, inclusive decision-making, augmented decision-making, and the creation of dynamic processes and resources for fast execution (Firat et al., 2010; Groche et al., 2019; Jin, 2021; Niemietz et al., 2020; Purr et al., 2015).

4.2.4.8 Body in White Manufacturing Planning and Simulation

"Body in white" (BIW) in manufacturing refers to the stage in the automotive production process where the car body's sheet metal components have been assembled but do not yet have any components, such as the engine or interior, installed. In other words, it is the stage where the car body is assembled and painted but is not yet a complete vehicle. The term "body in white" is derived from the fact that, at this stage, the car body is typically in its raw, unpainted state, often a white color, before further assembly and finishing processes occur.

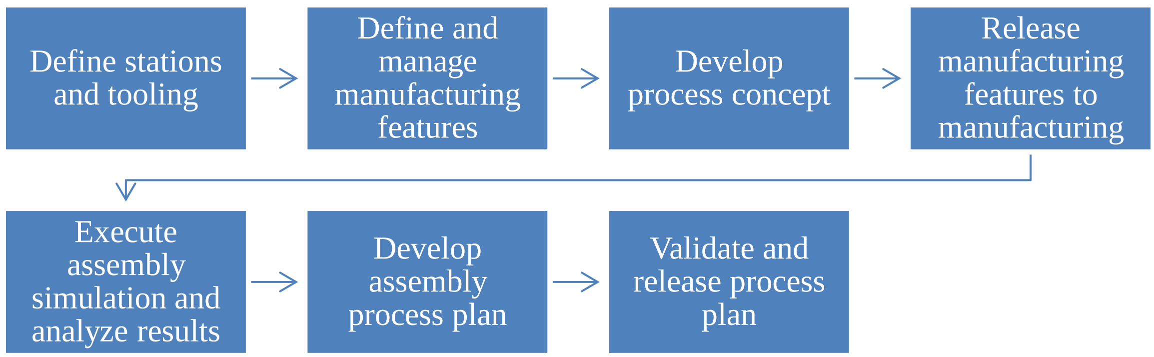

Figure 162 Typical Body in White Manufacturing Planning and Simulation Process Flow. Source: Author

The BIW stage is critical in automotive manufacturing as it sets the foundation for the final assembly of the vehicle. The Body in White Manufacturing Planning and Simulation function is integral to the manufacturing process, focusing on the planning and simulation aspects of Body in White (BiW) manufacturing. This function encompasses various activities as shown in *Figure 163*, such as defining stations and tooling, managing manufacturing features, developing process concepts, executing assembly simulations, and validating and releasing process plans.

Define Stations and Tooling: This activity involves the identification and specification of manufacturing stations and associated tooling required for the Body in White manufacturing process. Data science can aid in optimizing station layouts and tooling configurations by analyzing historical production data, minimizing bottlenecks, and enhancing overall production efficiency.

Define and Manage Manufacturing Features: Manufacturing features refer to specific attributes or characteristics of the product's design that impact the manufacturing process.

Data science can play a crucial role in managing these features by utilizing machine learning algorithms to analyze design data, predict manufacturing complexities, and optimize feature integration within the production process.

Develop Process Concept: The development of the process concept involves creating an overarching strategy for the Body in White manufacturing process. Data science contributes by analyzing historical process data, identifying best practices, and proposing innovative concepts to enhance manufacturing efficiency and product quality.

Release Manufacturing Features to Manufacturing: This activity involves the release of manufacturing features to the production floor. Data science facilitates this by implementing automated release processes, ensuring that the manufacturing features are seamlessly integrated into the production workflow based on real-time conditions and production demands.

Execute Assembly Simulation and Analyze Results: Assembly simulations are crucial for evaluating the feasibility and efficiency of the manufacturing process. Data science enables advanced simulation analytics by leveraging machine learning algorithms to analyze simulation results, identify potential issues, and optimize assembly sequences for improved performance.

Develop Assembly Process Plan: The development of the assembly process plan involves detailing the step-by-step procedures for Body in White manufacturing. Data science aids in this by analyzing historical assembly data, identifying optimal workflows, and recommending improvements to streamline the assembly process.

Validate and Release Process Plan: The validation and release of the process plan involves ensuring that the proposed assembly process is effective and aligns with quality standards. Data science supports this by implementing automated validation checks, analyzing real-time production data, and facilitating the seamless release of the finalized process plan.

The integration of data science into Body in White Manufacturing Planning and Simulation activities brings forth optimization and agility. Leveraging data-driven insights enhances the planning, simulation, and decision-making processes, fostering a more responsive, adaptive, and inclusive manufacturing environment. This approach aligns with the overarching goal of achieving business agility in Body in White manufacturing (Filz et al., 2020; Kibira et al., 2015; Meré et al., 2005; Shao et al., 2014; Vazan et al., 2017).

4.2.4.9 Additive Manufacturing Engineering & Print Preparation

The Additive Manufacturing Engineering & Print Preparation function is pivotal in harnessing the potential of additive manufacturing technologies. This section delves into the multifaceted activities conducted within this function as shown in *Figure 164*, ranging from 3D scanning to managing raw materials, along with insights on how data science can be instrumental in optimizing each activity. Additionally, a dedicated section explores how data science contributes to achieving specific business agility goals within this function.

The execution of 3D scanning involves capturing physical objects' geometric data to create precise digital representations. Data science can enhance this process through advanced algorithms that improve scanning accuracy and automate data processing, ensuring high-quality digital models.

Developing AM part concept design encompasses ideation and conceptualization for additive manufacturing. Data science aids in this phase by analyzing historical design data, market trends, and user preferences, offering valuable insights for innovative and optimized part concepts.

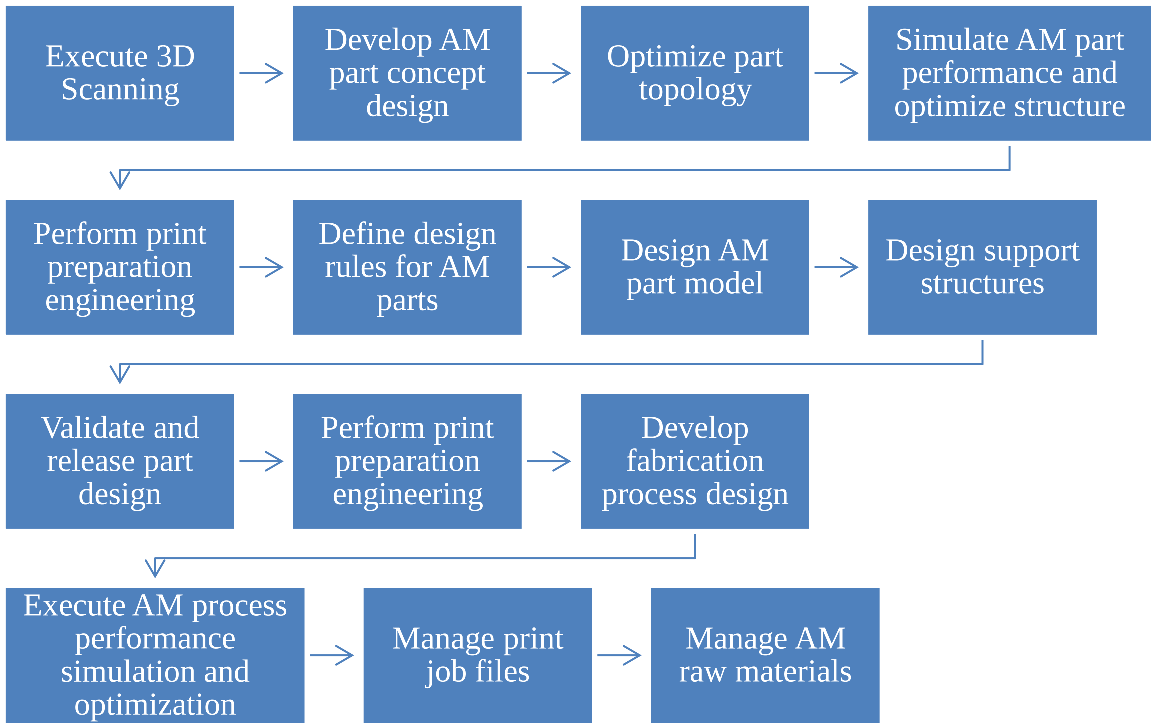

Figure 165 Typical Additive Manufacturing Engineering & Print Preparation Process Flow. Source: Author

Optimizing part topology involves refining the structure of the part to enhance performance and minimize material usage. Data science techniques, including topology optimization algorithms, play a crucial role in automating this process to achieve lightweight and structurally efficient designs.

Simulating AM part performance and optimizing structure employ data science for finite element analysis, predicting material behavior, and optimizing part geometry for enhanced performance. Machine learning models can expedite this simulation and optimization process.

Designing support structures and validating released part designs benefit from data science by automating the analysis of support structures' effectiveness and validating part designs against predefined criteria. This ensures the production of high-quality and structurally sound components.

Performing print preparation engineering involves the meticulous preparation of digital models for the additive manufacturing process. Data science can automate and optimize this engineering phase, ensuring efficient print preparation with minimal manual intervention.

Developing fabrication process design and executing AM process performance simulation and optimization leverage data science to model and optimize the additive manufacturing process. Machine learning algorithms can analyze process parameters and historical performance data to enhance efficiency.

Managing print job files and raw materials involves organizing and optimizing data related to printing tasks and material inventory. Data science contributes by implementing data-driven inventory management systems and optimizing print job scheduling for improved operational efficiency.

In conclusion, the integration of data science into the Additive Manufacturing Engineering & Print Preparation function enhances each activity from design optimization to print job management. Furthermore, data science contributes significantly to achieving business agility goals, fostering adaptive, informed decision-making and streamlined processes within the realm of additive manufacturing (Hashemi et al., 2022; Lu et al., 2017; Majeed et al., 2019; Pan & Hu, 2016; Winkler et al., 2020; Yan et al., 2018).

4.2.4.10 Hybrid Manufacturing Engineering & Preparation

The Hybrid Manufacturing Engineering & Preparation function is a crucial aspect of the broader operational framework, responsible for orchestrating various activities related to hybrid part design and fabrication. This section explores the key activities within this function as shown in *Figure 166*, delving into the design of hybrid part models, definition of design rules, simulation of hybrid part structures, definition of fabrication processes, and the execution of additive manufacturing print preparation, simulation, and fabrication.

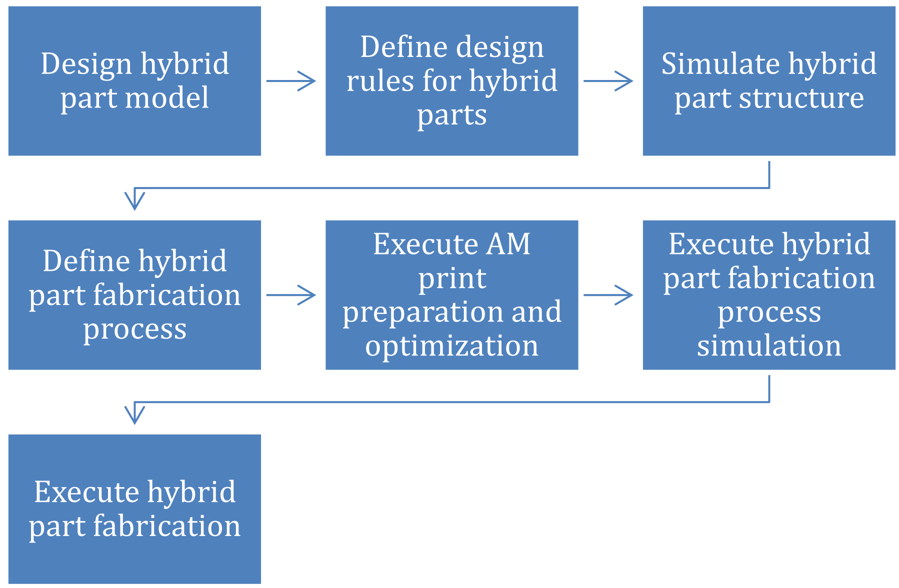

Figure 167 Typical Hybrid Manufacturing Engineering & Preparation Process Flow. Source: Author

Design Hybrid Part Model: This activity involves the creation of hybrid part models, integrating both additive manufacturing and traditional manufacturing components. Data science can enhance this process by utilizing generative design algorithms to explore multiple design iterations, optimizing for performance, cost, and manufacturability.

Define Design Rules for Hybrid Parts: Defining rules for hybrid part designs involves specifying constraints and guidelines to ensure the compatibility of additive and traditional manufacturing processes. Data science contributes by analyzing historical design data to establish rules that balance efficiency, structural integrity, and material compatibility.

Simulate Hybrid Part Structure: Simulation of hybrid part structures is crucial for assessing the performance and behavior of components under different conditions. Data science-driven simulations leverage Finite Element Analysis (FEA) and other techniques to predict structural responses, optimizing designs for various scenarios.

Define Hybrid Part Fabrication Process: Defining the fabrication process involves mapping out the sequence of manufacturing steps for hybrid parts. Data science supports this activity by analyzing historical process data, identifying bottlenecks, and optimizing the overall fabrication workflow for efficiency.

Execute Additive Manufacturing Print Preparation and Optimization: Executing additive manufacturing print preparation involves preparing digital models for physical fabrication. Data science contributes by automating print preparation tasks, optimizing printing parameters, and minimizing errors through machine learning algorithms.

Execute Hybrid Part Fabrication Process Simulation: Simulation of the hybrid part fabrication process ensures that the defined workflow aligns with expected outcomes. Data science facilitates this by conducting virtual simulations, identifying potential issues, and refining the fabrication process for optimal results.

Execute Hybrid Part Fabrication: The final activity involves the physical execution of the hybrid part fabrication process. Data science contributes by monitoring real-time manufacturing data, ensuring adherence to design specifications, and identifying opportunities for continuous improvement.

In conclusion, the Hybrid Manufacturing Engineering & Preparation function integrates data science into various activities related to hybrid part design and fabrication. Leveraging generative design, simulation, and AI-driven analytics, the function optimizes design processes, ensures efficient fabrication workflows, and enhances overall business agility. The use of data science fosters a responsive, user-centric environment, enables inclusive and augmented decision-making, and ensures dynamic processes and resources for fast execution in the dynamic landscape of hybrid manufacturing (Giess & Culley, 2003; Jain et al., 2017; Kibira et al., 2015; Popova et al., 2017; Wang et al., 2011).

4.2.4.11 Composite Engineering & Manufacturing

The Composite Engineering & Manufacturing function plays a crucial role in the design and production of composite materials, involving activities as shown in *Figure 168*, such as providing part design input, designing composite plans, simulating composite manufacturing processes, generating composite part programs, and managing releases to production.

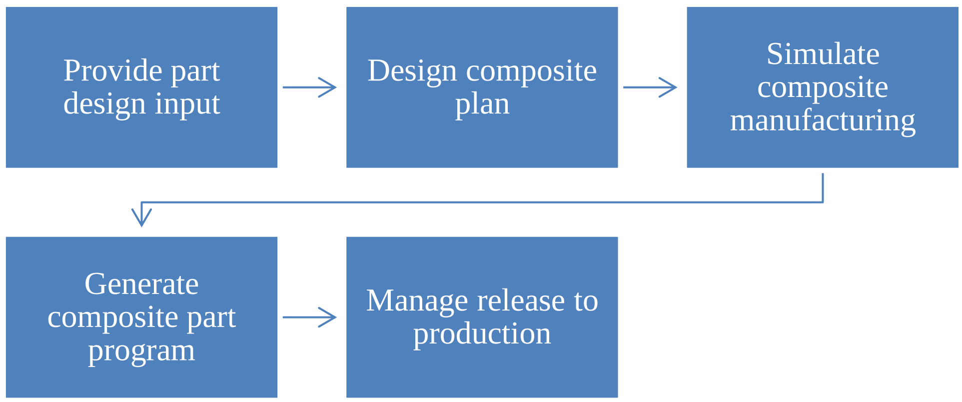

Figure 169 Typical Composite Engineering & Manufacturing function Process Flow. Source: Author

Part Design Input: This activity involves providing essential input for the design of composite parts. Data science can enhance this process by analyzing historical design data, predicting design trends, and offering recommendations for optimized part designs. Machine learning algorithms can assist in identifying patterns and correlations, ensuring that the design input aligns with the latest advancements and market demands.

Design Composite Plan: Designing a comprehensive plan for composite engineering is critical for successful manufacturing. Data science contributes by analyzing complex design parameters, historical manufacturing data, and market trends. Predictive modeling can optimize the composite plan, ensuring efficiency, cost-effectiveness, and compliance with industry standards.

Simulate Composite Manufacturing: Simulation is key to identifying potential issues in composite manufacturing before actual production begins. Data science supports this activity by implementing simulation models that analyze various manufacturing scenarios. Machine learning algorithms can predict potential challenges, allowing for proactive adjustments and improvements in the manufacturing process.

Generate Composite Part Program: Generating an effective part program is essential for translating design specifications into manufacturing instructions. Data science aids in this process by automating the generation of composite part programs. Machine learning models can analyze design data, historical production outcomes, and material properties to optimize part programs for efficiency and quality.

Manage Release to Production: This activity involves coordinating the release of composite designs to the production phase. Data science improves this process by implementing automated release management systems. Predictive analytics can assess factors such as production capacity, resource availability, and market demand to optimize the timing and efficiency of releasing designs to production.

In summary, the integration of data science into Composite Engineering & Manufacturing activities enhances various facets of the design and production processes. Leveraging data science contributes to improved part design, optimized composite plans, efficient manufacturing simulations, automated part program generation, and streamlined release management. Furthermore, the application of AI tools enhances business agility by improving behavioral and situational awareness, enabling inclusive and augmented decision-making, and creating dynamic processes and resources for fast execution in the dynamic landscape of composite engineering and manufacturing (Doreswamy, 2008; McMillan et al., 2017; Mojumder et al., 2021; Tekin & Kapan, 2016; Wiemer et al., 2017).

4.2.4.12 Mitigation Strategies for Challenges in Adoption of Data Science

In the manufacturing industry, data science plays a crucial role in optimizing various processes, improving decision-making, and enhancing business agility. This section provides an overview of how data science can be applied across different functions within a manufacturing planning department, specifically focusing on Electronics Specialized Manufacturing Process Planning. Each process is matched with relevant data science use cases and mapped to business agility goals. Additionally, potential challenges and associated risks are identified, along with mitigation strategies.

The **Manufacturing Assembly Planning and NPI for Electronics** process involves predicting maintenance needs for equipment, analytics for supply chain management, and optimization algorithms for production scheduling. These data science use cases contribute to improving situational awareness and enabling augmented decision-making. Challenges include a lack of skilled workforce, data quality issues, and integration complexities, which pose risks such as inaccurate predictions and compatibility issues. Mitigation strategies involve specialized training, rigorous data quality checks, and collaboration with IT. Table 20 summarizes the different data science use cases in this domain, associated challenges and risk along with the proposed mitigation strategies that can be taken by organizations.

Table 20 Data Science Use Cases for the various process in Manufacturing Assembly Planning and NPI for Electronics. Source: Author

Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Predictive maintenance for manufacturing equipment	- Improve Situational Awareness- Enable Augmented Decision Making	- Lack of skilled workforce- Data quality and availability- Integration with existing systems	- Inadequate expertise in predictive maintenance- Inaccurate or incomplete data for predictive modeling- Compatibility issues with existing systems	- Provide specialized training in predictive maintenance techniques- Implement rigorous data quality checks- Collaborate with IT for

Table 20 Data Science Use Cases for the various process in Manufacturing Assembly Planning and NPI for Electronics. Source: Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
				seamless integration
Predictive analytics for supply chain management	- Improve Behavioral Awareness- Enable Augmented Decision Making	- Data quality and availability- Privacy and security concerns- Lack of standardization	- Inaccurate or incomplete data for analysis- Data privacy risks- Lack of standardized analytical protocols	- Implement rigorous data quality checks- Ensure compliance with data privacy regulations- Develop standardized analytical protocols
Optimization algorithms for production scheduling	- Create Dynamic Processes for Fast Execution	- Lack of skilled workforce- Integration with existing systems- Scalability	- Inadequate expertise in optimization algorithms- Integration challenges with existing systems- Scalability issues with large datasets	- Provide specialized training in optimization techniques- Explore scalable data storage and processing solutions- Collaborate

Table 20 Data Science Use Cases for the various process in Manufacturing Assembly Planning and NPI for Electronics. Source: Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
				with IT for seamless integration

For PCD Design for manufacturing (DFM), data science methods like machine learning for design optimization and predictive modeling for design verification are utilized to improve situational awareness and enable augmented decision-making. Challenges related to data quality and privacy risks require strategies such as rigorous data quality checks and compliance with privacy regulations. Table 21 summarizes the different data science use cases in this domain, associated challenges and risk along with the proposed mitigation strategies that can be taken by organizations.

Table 21 Data Science Use Cases for the various process in PCD Design for manufacturing (DFM). Source: Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Machine learning for design optimization	- Improve Situational Awareness - Enable Augmented Decision Making	- Lack of skilled workforce - Data quality and availability - Integration with existing systems	- Inadequate expertise in machine learning - Inaccurate or incomplete data for modeling - Compatibility issues with existing systems	- Provide specialized training in machine learning techniques - Implement rigorous data quality checks- Collaborate with IT for seamless integration

Table 21 Data Science Use Cases for the various process in PCD Design for manufacturing (DFM). Source: Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Predictive modeling for design verification	- Improve Situational Awareness - Enable Augmented Decision Making	- Data quality and availability - Privacy and security concerns - Lack of standardization	- Inaccurate or incomplete data for modeling - Data privacy risks - Lack of standardized modeling protocols	- Implement rigorous data quality checks - Ensure compliance with data privacy regulations - Develop standardized modeling protocols
Simulation-based design validation	- Create Dynamic Processes for Fast Execution	- Lack of skilled workforce - Data quality and availability - Integration with existing systems	- Inadequate expertise in simulation techniques - Inaccurate or incomplete data for simulation - Compatibility issues with existing systems	- Provide specialized training in simulation techniques - Implement rigorous data quality checks - Collaborate with IT for seamless integration

Harness Manufacturing Planning & Simulation involves defining the assembly process, assigning parts and resources, and simulating the manufacturing workflow. Data science enables predictive modeling for process optimization and simulation-based validation, enhancing situational awareness and decision-making. Challenges include data quality issues and integration complexities, mitigated through rigorous data quality checks and collaboration with IT for seamless integration. Table 22 summarizes the different data science use cases in this domain, associated challenges and risk along with the proposed mitigation strategies that can be taken by organizations.

Table 22 Data Science Use Cases for the various process in Harness Manufacturing Planning & Simulation. Source : Author

Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Machine learning for predictive maintenance of manufacturing equipment	- Improve Situational Awareness- Enable Augmented Decision Making	- Lack of skilled workforce- Data quality and availability- Integration with existing systems	- Inadequate expertise in machine learning- Inaccurate or incomplete data for predictive modeling- Compatibility issues with existing systems	- Provide specialized training in machine learning techniques- Implement rigorous data quality checks- Collaborate with IT for seamless integration
Predictive analytics for material procurement	- Improve Behavioral Awareness- Enable Augmented Decision Making	- Data quality and availability- Privacy and security concerns- Lack of standardization	- Inaccurate or incomplete data for analysis- Data privacy risks- Lack of standardized analytical protocols	- Implement rigorous data quality checks- Ensure compliance with data privacy regulations-

Table 22 Data Science Use Cases for the various process in Harness Manufacturing Planning & Simulation. Source : Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
				Develop standardized analytical protocols
Optimization algorithms for production scheduling	- Create Dynamic Processes for Fast Execution	- Lack of skilled workforce- Integration with existing systems- Scalability	- Inadequate expertise in optimization algorithms- Integration challenges with existing systems- Scalability issues with large datasets	- Provide specialized training in optimization techniques- Explore scalable data storage and processing solutions- Collaborate with IT for seamless integration

In Tape-out Management, predictive modeling for tape-out optimization and simulation-based design validation contribute to improving situational awareness and creating dynamic processes for fast execution. Table 23 summarizes the different data science use cases in this domain, associated challenges and risk along with the proposed mitigation strategies that can be taken by organizations.

Table 23 Data Science Use Cases for the various process in Tape-out Management. Source: Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Predictive modeling for tape-out optimization	- Improve Situational Awareness- Enable Augmented Decision Making	- Lack of skilled workforce- Data quality and availability- Integration with existing systems	- Inadequate expertise in predictive modeling- Inaccurate or incomplete data for modeling- Compatibility issues with existing systems	- Provide specialized training in predictive modeling techniques- Implement rigorous data quality checks- Collaborate with IT for seamless integration
Machine learning for identifying design flaws	- Improve Situational Awareness- Enable Augmented Decision Making	- Data quality and availability- Privacy and security concerns- Lack of standardization	- Inaccurate or incomplete data for analysis- Data privacy risks- Lack of standardized anomaly detection protocols	- Implement rigorous data quality checks- Ensure compliance with data privacy regulations- Develop standardized anomaly detection protocols

Table 23 Data Science Use Cases for the various process in Tape-out Management. Source: Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Simulation-based tape-out validation	- Create Dynamic Processes for Fast Execution	- Lack of skilled workforce- Data quality and availability- Integration with existing systems	- Inadequate expertise in simulation techniques- Inaccurate or incomplete data for simulation- Compatibility issues with existing systems	- Provide specialized training in simulation techniques- Implement rigorous data quality checks- Collaborate with IT for seamless integration

Challenges include a lack of skilled workforce and integration issues, which can be mitigated through specialized training and collaboration with IT for seamless integration.

IC Manufacturing, Packaging & Test relies on data science for predictive maintenance of manufacturing equipment and predictive analytics for quality control. These use cases aim to improve situational awareness and enable augmented decision-making. Challenges such as data quality and integration complexities can be mitigated through rigorous data quality checks and collaboration with IT for seamless integration. Table 24 summarizes the different data science use cases in this domain, associated challenges and risk along with the proposed mitigation strategies that can be taken by organizations.

Table 24 Data Science Use Cases for the various process in IC Manufacturing, Packaging & Test. Source:Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Predictive maintenance for manufacturing equipment	- Improve Situational Awareness- Enable Augmented Decision Making	- Lack of skilled workforce- Data quality and availability- Integration with existing systems	- Inadequate expertise in predictive maintenance- Inaccurate or incomplete data for predictive modeling- Compatibility issues with existing systems	- Provide specialized training in predictive maintenance techniques- Implement rigorous data quality checks- Collaborate with IT for seamless integration
Predictive analytics for yield optimization	- Improve Situational Awareness- Enable Augmented Decision Making	- Data quality and availability- Privacy and security concerns- Lack of standardization	- Inaccurate or incomplete data for analysis- Data privacy risks- Lack of standardized analytical protocols	- Implement rigorous data quality checks- Ensure compliance with data privacy regulations- Develop standardized analytical protocols

Table 24 Data Science Use Cases for the various process in IC Manufacturing, Packaging & Test. Source:Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Simulation-based test strategy optimization	- Create Dynamic Processes for Fast Execution	- Lack of skilled workforce- Data quality and availability- Integration with existing systems	- Inadequate expertise in simulation techniques- Inaccurate or incomplete data for simulation- Compatibility issues with existing systems	- Provide specialized training in simulation techniques- Implement rigorous data quality checks- Collaborate with IT for seamless integration

Mold, Tool & Die Design Management utilizes machine learning for predictive maintenance and simulation-based design validation to improve situational awareness and enable augmented decision-making. Challenges related to data quality and lack of standardization can be addressed through specialized training and implementing standardized protocols. Table 25 summarizes the different data science use cases in this domain, associated challenges and risk along with the proposed mitigation strategies that can be taken by organizations.

Table 25 Data Science Use Cases for the various process in Mold, Tool & Die Design Management. Source: Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Machine learning for predictive maintenance of tooling and dies	Improve Situational Awareness- Enable Augmented Decision Making	Lack of skilled workforce- Data quality and availability- Integration with existing systems	Inadequate expertise in machine learning- Inaccurate or incomplete data for predictive modeling- Compatibility issues with existing systems	Provide specialized training in machine learning techniques- Implement rigorous data quality checks- Collaborate with IT for seamless integration
Predictive analytics for tooling and die wear prediction	Improve Situational Awareness- Enable Augmented Decision Making	Data quality and availability- Privacy and security concerns- Lack of standardization	Inaccurate or incomplete data for analysis- Data privacy risks- Lack of standardized analytical protocols	Implement rigorous data quality checks- Ensure compliance with data privacy regulations- Develop standardized analytical protocols
Simulation-based tooling and die design validation	Create Dynamic Processes for Fast Execution	Lack of skilled workforce- Data quality and availability- Integration with existing systems	Inadequate expertise in simulation techniques- Inaccurate or incomplete data for simulation- Compatibility issues with existing systems	Provide specialized training in simulation techniques- Implement rigorous data quality checks- Collaborate with IT for seamless integration

In Body Manufacturing Stamping, predictive maintenance for stamping equipment and predictive analytics for quality control contribute to improving situational awareness and enabling augmented decision-making. Challenges such as a lack of skilled workforce and data quality issues can be mitigated through specialized training and rigorous data quality checks. Table 26 summarizes the different data science use cases in this domain, associated challenges and risk along with the proposed mitigation strategies that can be taken by organizations.

Table 26 Data Science Use Cases for the various process in Body Manufacturing Stamping. Source:Author

Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Predictive maintenance for stamping equipment	- Improve Situational Awareness- Enable Augmented Decision Making	- Lack of skilled workforce- Data quality and availability- Integration with existing systems	- Inadequate expertise in predictive maintenance- Inaccurate or incomplete data for predictive modeling- Compatibility issues with existing systems	- Provide specialized training in predictive maintenance techniques- Implement rigorous data quality checks- Collaborate with IT for seamless integration
Predictive analytics for quality control and defect detection	- Improve Situational Awareness- Enable Augmented Decision Making	- Data quality and availability- Privacy and security concerns- Lack of standardization	- Inaccurate or incomplete data for analysis- Data privacy risks- Lack of standardized analytical protocols	- Implement rigorous data quality checks- Ensure compliance with data privacy regulations-

Table 26 Data Science Use Cases for the various process in Body Manufacturing Stamping. Source:Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
				Develop standardized analytical protocols
Simulation-based stamping process optimization	- Create Dynamic Processes for Fast Execution	- Lack of skilled workforce- Data quality and availability- Integration with existing systems	- Inadequate expertise in simulation techniques- Inaccurate or incomplete data for simulation- Compatibility issues with existing systems	- Provide specialized training in simulation techniques- Implement rigorous data quality checks- Collaborate with IT for seamless integration

Body in White (BIW) Manufacturing Planning and Simulation encompasses the planning and simulation of the initial vehicle structure assembly process. Data science is utilized for predictive modeling to optimize manufacturing processes and for simulation-based validation to ensure efficient assembly. This enhances situational awareness and facilitates augmented decision-making. Challenges may arise from data quality and integration issues, which can be addressed through rigorous data quality checks and collaboration with IT for seamless integration. Table 27 summarizes the different data science use cases in this domain, associated challenges and risk along with the proposed mitigation strategies that can be taken by organizations.

Table 27 Data Science Use Cases for the various process in Body in White (BIW) Manufacturing Planning and Simulation. Source:Author

Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Machine learning for predictive maintenance of manufacturing equipment	- Improve Situational Awareness- Enable Augmented Decision Making	- Lack of skilled workforce- Data quality and availability- Integration with existing systems	- Inadequate expertise in machine learning- Inaccurate or incomplete data for predictive modeling- Compatibility issues with existing systems	- Provide specialized training in machine learning techniques- Implement rigorous data quality checks- Collaborate with IT for seamless integration
Predictive analytics for quality control and defect detection	- Improve Situational Awareness- Enable Augmented Decision Making	- Data quality and availability- Privacy and security concerns- Lack of standardization	- Inaccurate or incomplete data for analysis- Data privacy risks- Lack of standardized analytical protocols	- Implement rigorous data quality checks- Ensure compliance with data privacy regulations- Develop standardized analytical protocols

Table 27 Data Science Use Cases for the various process in Body in White (BIW) Manufacturing Planning and Simulation. Source:Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Simulation-based manufacturing process optimization	- Create Dynamic Processes for Fast Execution	- Lack of skilled workforce- Data quality and availability- Integration with existing systems	- Inadequate expertise in simulation techniques- Inaccurate or incomplete data for simulation- Compatibility issues with existing systems	- Provide specialized training in simulation techniques- Implement rigorous data quality checks- Collaborate with IT for seamless integration

Additive Manufacturing Engineering & Print Preparation involves the preparation and optimization of designs for additive manufacturing processes. Data science is applied for predictive modeling to optimize print parameters and for simulation-based validation of print outcomes. This enhances situational awareness and facilitates augmented decision-making in selecting the most efficient printing strategies. Challenges may include data quality issues and integration complexities, which can be mitigated through rigorous data quality checks and collaboration with IT for seamless integration. Table 28 summarizes the different data science use cases in this domain, associated challenges and risk along with the proposed mitigation strategies that can be taken by organizations.

Table 28 Data Science Use Cases for the various process in Additive Manufacturing Engineering & Print Preparation. Source: Author

Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Machine learning for optimizing print parameters	- Improve Situational Awareness- Enable Augmented Decision Making	- Lack of skilled workforce- Data quality and availability- Integration with existing systems	- Inadequate expertise in machine learning- Inaccurate or incomplete data for modeling- Compatibility issues with existing systems	- Provide specialized training in machine learning techniques- Implement rigorous data quality checks- Collaborate with IT for seamless integration
Predictive modeling for print quality prediction	- Improve Situational Awareness- Enable Augmented Decision Making	- Data quality and availability- Privacy and security concerns- Lack of standardization	- Inaccurate or incomplete data for modeling- Data privacy risks- Lack of standardized modeling protocols	- Implement rigorous data quality checks- Ensure compliance with data privacy regulations- Develop standardized modeling protocols
Simulation-based print process optimization	- Create Dynamic Processes for Fast Execution	- Lack of skilled workforce- Data quality and	- Inadequate expertise in simulation techniques- Inaccurate or	- Provide specialized training in simulation techniques-

Table 28 Data Science Use Cases for the various process in Additive Manufacturing Engineering & Print Preparation. Source: Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
		availability- Integration with existing systems	incomplete data for simulation- Compatibility issues with existing systems	Implement rigorous data quality checks- Collaborate with IT for seamless integration

Hybrid Manufacturing Engineering & Preparation encompasses the planning and optimization of hybrid manufacturing processes, which combine additive and subtractive manufacturing techniques. Data science is utilized for predictive modeling to optimize process parameters and for simulation-based validation of manufacturing outcomes. This enhances situational awareness and enables augmented decision-making in selecting the most effective manufacturing strategies. Challenges may include data quality issues and integration complexities, which can be mitigated through rigorous data quality checks and collaboration with IT for seamless integration. Table 29 summarizes the different data science use cases in this domain, associated challenges and risk along with the proposed mitigation strategies that can be taken by organizations.

Table 29 Data Science Use Cases for the various process in Hybrid Manufacturing Engineering & Preparation. Source: Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Predictive maintenance for hybrid manufacturing equipment	- Improve Situational Awareness- Enable Augmented	- Lack of skilled workforce- Data quality and availability- Integration with existing systems	- Inadequate expertise in predictive maintenance- Inaccurate or incomplete data	- Provide specialized training in predictive maintenance techniques-

Table 29 Data Science Use Cases for the various process in Hybrid Manufacturing Engineering & Preparation. Source: Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
	Decision Making		for predictive modeling- Compatibility issues with existing systems	Implement rigorous data quality checks- Collaborate with IT for seamless integration
Predictive analytics for material selection and process optimization	- Improve Situational Awareness- Enable Augmented Decision Making	- Data quality and availability- Privacy and security concerns- Lack of standardization	- Inaccurate or incomplete data for analysis- Data privacy risks- Lack of standardized analytical protocols	- Implement rigorous data quality checks- Ensure compliance with data privacy regulations- Develop standardized analytical protocols
Simulation-based hybrid manufacturing process optimization	- Create Dynamic Processes for Fast Execution	- Lack of skilled workforce- Data quality and availability- Integration with existing systems	- Inadequate expertise in simulation techniques- Inaccurate or incomplete data	- Provide specialized training in simulation techniques- Implement

Table 29 Data Science Use Cases for the various process in Hybrid Manufacturing Engineering & Preparation. Source: Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
			for simulation- Compatibility issues with existing systems	rigorous data quality checks- Collaborate with IT for seamless integration

Composite Engineering & Manufacturing involves the design and production of composite materials for various applications. Data science is applied for predictive modeling to optimize material properties and manufacturing processes. Additionally, simulation-based validation ensures the efficiency and quality of composite structures. This enhances situational awareness and enables augmented decision-making in material selection and process optimization. Challenges may arise from data quality issues and integration complexities, which can be mitigated through rigorous data quality checks and collaboration with IT for seamless integration. Table 30 summarizes the different data science use cases in this domain, associated challenges and risk along with the proposed mitigation strategies that can be taken by organizations.

Table 30 Data Science Use Cases for the various process in Composite Engineering & Manufacturing. Source: Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Machine learning for composite material design	- Improve Situational Awareness- Enable Augmented	- Lack of skilled workforce- Data quality and	- Inadequate expertise in machine learning- Inaccurate or	- Provide specialized training in machine learning techniques-

Table 30 Data Science Use Cases for the various process in Composite Engineering & Manufacturing. Source: Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
and optimization	Decision Making	availability- Integration with existing systems	incomplete data for modeling- Compatibility issues with existing systems	Implement rigorous data quality checks- Collaborate with IT for seamless integration
Predictive modeling for composite manufacturing process optimization	- Improve Situational Awareness- Enable Augmented Decision Making	- Data quality and availability- Privacy and security concerns- Lack of standardization	- Inaccurate or incomplete data for modeling- Data privacy risks- Lack of standardized modeling protocols	- Implement rigorous data quality checks- Ensure compliance with data privacy regulations- Develop standardized modeling protocols
Simulation-based composite manufacturing process validation	- Create Dynamic Processes for Fast Execution	- Lack of skilled workforce- Data quality and availability- Integration with existing systems	- Inadequate expertise in simulation techniques- Inaccurate or incomplete data for simulation- Compatibility	- Provide specialized training in simulation techniques- Implement rigorous data quality checks- Collaborate with

Table 30 Data Science Use Cases for the various process in Composite Engineering & Manufacturing. Source: Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
			issues with existing systems	IT for seamless integration

In summary, data science is instrumental in optimizing Electronics Specialized Manufacturing Process Planning. Through advanced analytics, predictive modeling, and simulation techniques, manufacturers can enhance operations like assembly planning, design for manufacturing, and tape-out management. While data quality and integration challenges exist, effective mitigation strategies ensure the full utilization of data science's potential. By overcoming these obstacles, organizations can drive innovation, competitiveness, and agility in the electronics manufacturing sector, ultimately achieving greater efficiency and productivity in their processes.

4.3 Mitigation Strategies for Challenges in Adoption of Data Science in Manufacturing Engineering

In the multifaceted domain of Manufacturing Engineering, the infusion of data science emerges as a transformative force across key business processes. The realm of Manufacturing Systems Design involves intricate activities such as Manufacturing Line Design, Collaborative Automation Design for Manufacturing Line, Collaborative Automation Design for Manufacturing Machine, Machine Tool Automation Design, and Machine Tool Electrical Design. Concurrently, the Automation Engineering & Commissioning function encompasses a spectrum of tasks from Automation Engineering and Project Management to Virtual Commissioning for Material Handling and Warehousing, Production Lines (Robot Cells), Production Machines, and Machine Tools. The Manufacturing Building and Asset Management facet contribute to the seamless operation of the manufacturing environment through activities like Construction Planning and Simulation, Building Design Management, Plant Asset Management, Plant Design, Utilities Planning and Engineering, Factory Electrification planning and Engineering, Industrial Energy Management, and Liquids & Gas Flow Simulation. In each of these functional areas, the application of data science methodologies introduces opportunities for advanced analytics, predictive modelling, and optimization. This data-centric approach enhances decision support mechanisms, augments process efficiency, and elevates overall performance within the Manufacturing Engineering discipline.

Furthermore, data science integration offers a strategic advantage in Manufacturing Systems Design by facilitating comprehensive analysis and optimization of manufacturing line configurations, collaborative automation setups, and machine tool designs. In Automation Engineering & Commissioning, data science enhances project management, industrial communication, recognition and identification processes, and virtual commissioning for various aspects, leading to more efficient and responsive automation solutions. The application of data science methodologies in Manufacturing Building and Asset Management transforms construction planning, building design, plant asset management, and energy-related processes. This results in improved simulations, better utilities planning, and more effective electrification strategies.

The synergy between data science and Manufacturing Engineering is particularly evident in predictive maintenance for machinery, real-time monitoring of industrial processes, and the optimization of material transportation systems. Predictive modelling aids in identifying potential issues before they escalate, reducing downtime and maintenance costs. Real-time monitoring, enabled by data science, ensures the agile response to dynamic production conditions, contributing to enhanced overall operational efficiency.

The incorporation of data science within the Manufacturing Engineering function opens new avenues for innovation, process refinement, and strategic decision-making. It underscores the evolving role of technology in fostering agility, sustainability, and competitiveness within the manufacturing landscape.

Moreover, data science acts as a catalyst for transformative advancements in Manufacturing Engineering by introducing machine learning algorithms and artificial intelligence into the automation landscape. These technologies enable adaptive control, self-optimization, and the ability to learn from historical data, thereby refining automation processes over time. Virtual commissioning, backed by data-driven simulations, facilitates thorough testing and validation of automation setups before physical implementation, reducing errors and accelerating deployment timelines.

In Manufacturing Systems Design, the utilization of data science techniques enables predictive modelling for production line efficiency, collaborative automation effectiveness, and machine tool performance. This proactive approach empowers engineers to make informed decisions, adjust designs based on dynamic insights, and continuously enhance manufacturing processes for optimal outcomes.

Additionally, the integration of data science in Manufacturing Building and Asset Management supports intelligent resource allocation, energy-efficient planning, and sustainability initiatives. Through advanced analytics, the optimization of plant layouts, utilities planning, and energy management becomes more precise, contributing to eco-friendly practices and cost-effective resource utilization.

In conclusion, the symbiosis of data science and Manufacturing Engineering not only enhances existing processes but also paves the way for innovative solutions and adaptive strategies. As the manufacturing landscape evolves, the strategic application of data science proves instrumental in fostering resilience, agility, and sustainable growth within the realm of Manufacturing Engineering (Feng et al., 2009; Kibira et al., 2015; Pullan et al., 2012; Qin & Dong, 2020; Volpentesta et al., 2004).

4.3.1 Mitigation Strategies for Challenges in Adoption of Data Science in Manufacturing Systems Design

In the realm of Manufacturing Systems Design, data science emerges as a transformative tool, offering valuable insights and enhancements across various sub-functions shown in *Figure 170*. These sub-functions play a pivotal role in shaping a comprehensive approach to manufacturing engineering.

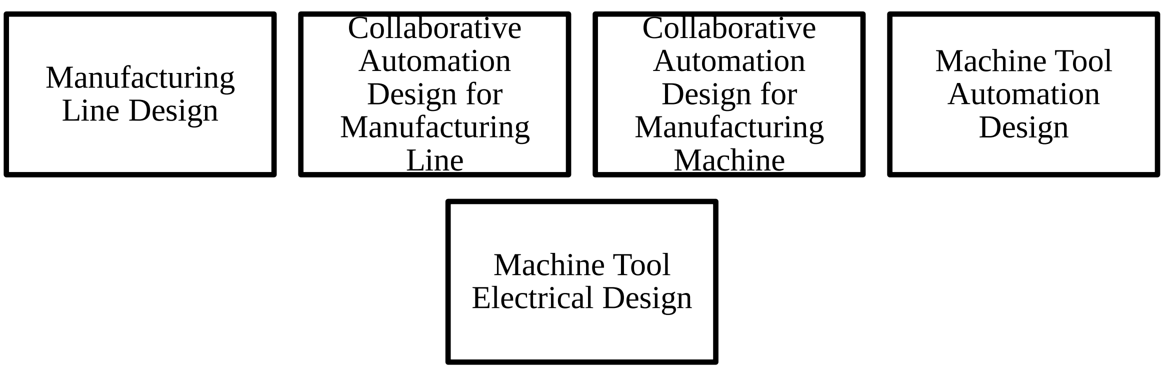

Figure 171 Manufacturing Systems Design Sub Functions. Source: Author

The infusion of data science into Manufacturing Systems Design is transformative, offering a data-driven approach to decision-making and problem-solving. By harnessing the power of predictive analytics, optimization algorithms, and real-time data analysis, manufacturing engineers can design systems that are not only efficient but also adaptable to the dynamic and evolving nature of modern manufacturing environments. As the industry embraces the principles of Industry 4.0, the role of data science in Manufacturing Systems Design becomes increasingly indispensable for achieving operational excellence and staying competitive in a rapidly changing global market (Qin & Dong, 2020; Kibira et al., 2015; Pullan et al., 2012; Feng et al., 2009; Volpentesta et al., 2004).

4.3.1.1 Manufacturing Line Design

The Manufacturing Line Design function encompasses a series of activities as shown in *Figure 172* which are crucial for optimizing the layout and efficiency of manufacturing lines. These activities range from initial planning to detailed design and integration, ensuring that the manufacturing processes are streamlined and aligned with operational goals.

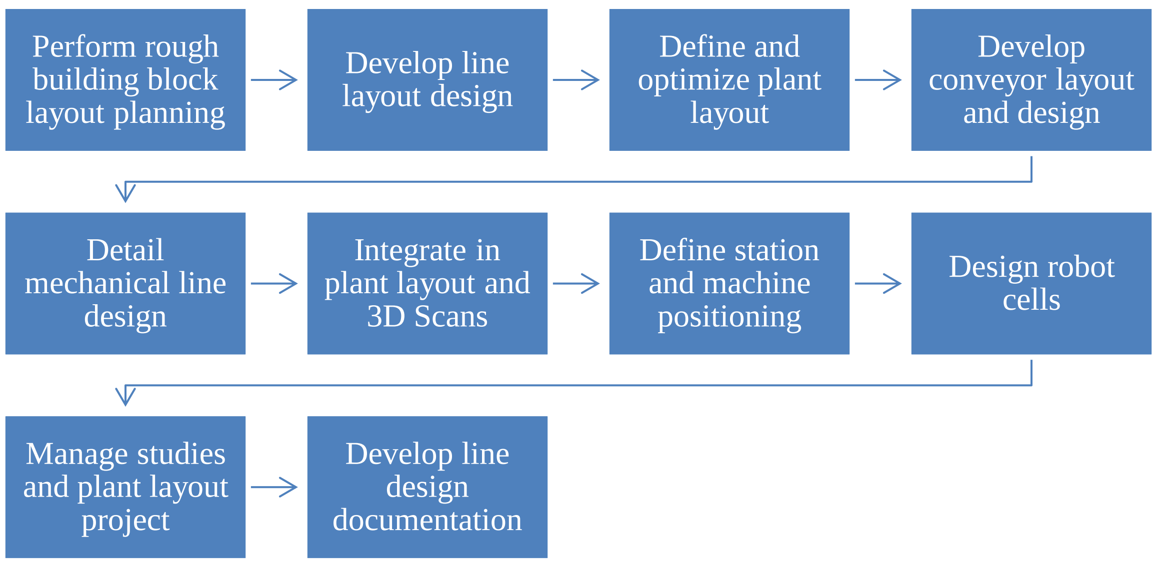

Figure 173 Typical Manufacturing Line Design Function Process Flow. Source: Author

Perform Rough Building Block Layout Planning: This initial step involves a high-level layout planning, outlining the rough building blocks of the manufacturing line. Data science can contribute by analyzing historical production data, optimizing space utilization, and predicting potential bottlenecks, providing valuable insights for an effective layout plan.

Develop Line Layout Design: The development of line layout design involves creating a blueprint for the manufacturing line. Data science applications, such as simulation models, can assist in optimizing the layout for efficiency by considering factors like material flow, workstation arrangements, and equipment placement.

Define and Optimize Plant Layout: Plant layout definition and optimization involve considering the overall arrangement of workspaces and facilities. Data science algorithms can analyze spatial relationships, historical performance data, and production requirements to optimize the plant layout for maximum efficiency and resource utilization.

Develop Conveyor Layout and Design: Conveyor layout and design require careful consideration of material flow and transportation within the manufacturing line. Data science can contribute by analyzing real-time data on material movement, predicting optimal conveyor configurations, and ensuring smooth material handling.

Detail Mechanical Line Design: The detailed mechanical design involves specifying the components and mechanisms of the manufacturing line. Data science can assist in this phase by analyzing design parameters, historical mechanical performance data, and industry standards to optimize the mechanical components for reliability and performance.

Integrate in Plant Layout and 3D Scans: Integration into plant layout involves incorporating the manufacturing line design into the overall plant layout. Data science, in collaboration with 3D scanning technologies, can ensure accurate integration by analyzing spatial relationships, optimizing placement, and validating the design within the broader plant infrastructure.

Define Station and Machine Positioning: Defining station and machine positioning is critical for efficient workflow and production. Data science algorithms can analyze production data, machine capabilities, and historical performance to optimize station and machine placements for maximum productivity.

Design Robot Cells: Designing robot cells involves integrating robotic systems into the manufacturing line. Data science can contribute by analyzing production requirements, robot capabilities, and historical data to optimize robot cell design for automation efficiency.

Manage Studies and Plant Layout Projects: Project management for studies and plant layout projects involves coordinating various aspects of the design process. Data science can assist by providing project management insights, optimizing resource allocation, and predicting project timelines based on historical project data.

Develop Line Design Documentation: The development of line design documentation ensures that the manufacturing line design is well-documented for future reference. Data science can assist in this phase by automating documentation processes, ensuring accuracy, and facilitating easy retrieval of design information.

In conclusion, the Manufacturing Line Design function, with its diverse activities from initial planning to detailed design, benefits significantly from the integration of data science. The application of data science enhances efficiency, optimizes resource utilization, and contributes to overall business agility by improving behavioral awareness, situational awareness, decision-making inclusivity, augmented decision-making, and the creation of dynamic processes and resources for fast execution (Agard & Cunha, 2007; Borja et al., 2001; Popova et al., 2017; Qin & Dong, 2020; Vodencarevic & Fett, 2015).

4.3.1.2 Collaborative Automation Design for Manufacturing Line

The Collaborative Automation Design for Manufacturing Line function encompasses a series of critical activities as shown in *Figure 174* aimed at optimizing the design and implementation of automated manufacturing processes.

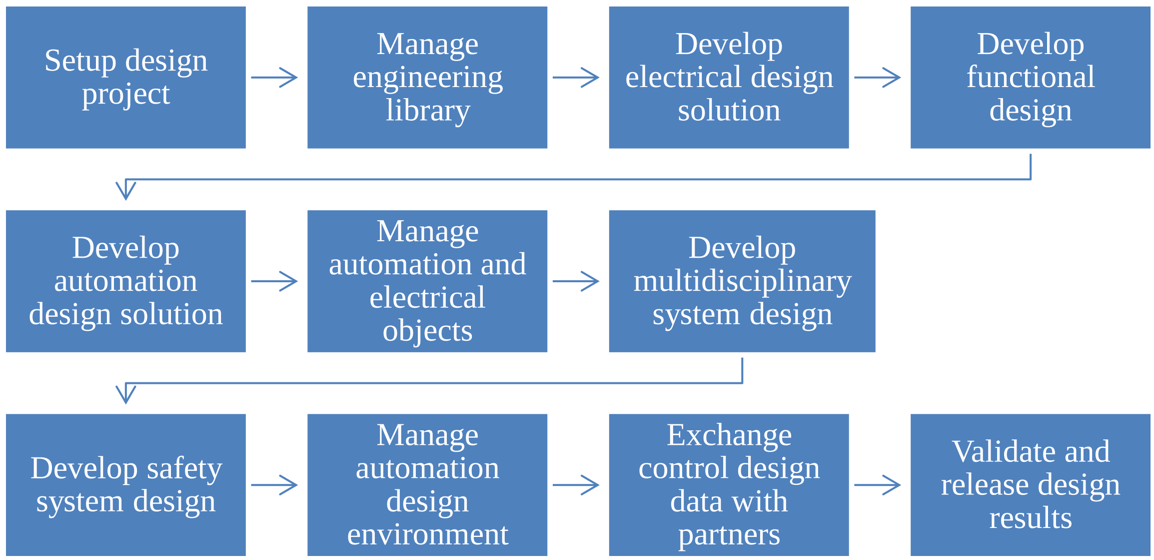

Figure 175 Collaborative Automation Design for Manufacturing Line Process Flow. Source: Author

This section delves into the multifaceted tasks within this function and explores how data science can be strategically employed to enhance these processes.

Setup Design Project: Initiating the design project involves defining project parameters, objectives, and scope. Data science contributes by analyzing historical project data to recommend optimal setups, ensuring efficient project initiation.

Manage Engineering Library: Efficient library management involves organizing, updating, and retrieving engineering data. Data science aids in managing engineering libraries by implementing automated categorization, version control, and intelligent search capabilities, improving accessibility and accuracy.

Develop Electrical Design Solution: Creating electrical design solutions involves specifying electrical components and configurations. Data science supports this activity by analyzing historical design data, suggesting optimized solutions, and predicting potential issues to enhance the overall electrical design process.

Develop Functional Design: Functional design development focuses on defining system functions and interactions. Data science assists by analyzing requirements, user data, and historical functional design data, facilitating the creation of more robust and effective functional designs.

Develop Automation Design Solution: Creating automation design solutions requires specifying control systems and interfaces. Data science contributes by analyzing historical automation design data, optimizing control strategies, and suggesting improvements for increased efficiency.

Manage Automation and Electrical Objects: Efficient management of automation and electrical objects involves organizing and maintaining a repository of design elements. Data science aids in automated object categorization, version control, and predictive maintenance, ensuring a streamlined management process.

Develop Multidisciplinary System Design: Multidisciplinary system design integrates various engineering disciplines. Data science supports this by analyzing cross-disciplinary data, identifying interdependencies, and providing insights to enhance the cohesion of system designs.

Develop Safety System Design: Safety system design involves defining and implementing safety measures within the automation process. Data science contributes by analyzing safety data, identifying potential risks, and recommending safety strategies to ensure compliance and mitigate hazards.

Manage Automation Design Environment: Efficiently managing the automation design environment involves configuring software tools and interfaces. Data science contributes by analyzing user interactions, suggesting interface improvements, and optimizing the design environment for enhanced usability.

Exchange Control Design Data with Partners: Collaborative data exchange with partners requires seamless communication and data interoperability. Data science supports this by implementing data standardization, facilitating real-time data exchange, and optimizing data compatibility with partner systems.

Validate and Release Design Results: The validation and release of design results involve ensuring that designs meet specified requirements. Data science contributes by automating validation processes, predicting potential design issues, and facilitating a more informed and efficient release process.

In conclusion, the Collaborative Automation Design for Manufacturing Line function involves a spectrum of activities crucial for effective automation implementation. The strategic integration of data science optimizes these processes, fostering improved efficiency, collaboration, and decision-making. Furthermore, leveraging AI tools enhances business agility by improving behavioral awareness, situational awareness, decision inclusivity, decision augmentation, and creating dynamic processes and resources for fast execution. This holistic approach ensures a more agile and responsive manufacturing line design environment (Morinaga et al., 2006; Nagy et al., 2022; Noel & Brissaud, 2003; Sibona & Indri, 2021; Weiming Shen et al., 2005).

4.3.1.3 Collaborative Automation Design for Manufacturing Machine

The Collaborative Automation Design for Manufacturing Machine function encompasses a spectrum of activities as shown in *Figure 176* which are crucial for the efficient design and implementation of automated manufacturing processes. This section delves into the diverse range of tasks this function performs, elucidating each activity and exploring the role of data science in optimizing these processes.

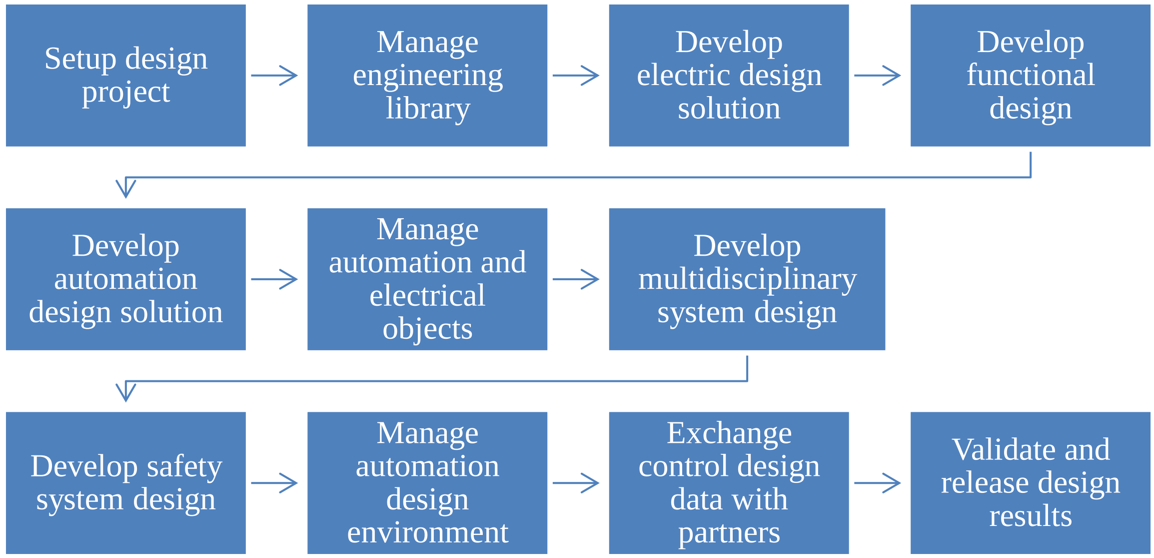

Figure 177 Collaborative Automation Design for Manufacturing Machine Process Flow. Source: Author

Setup Design Project: Initiating the design process involves setting up comprehensive design projects. Data science can facilitate this by analyzing historical project data to optimize project configurations, streamline resource allocation, and enhance overall project planning.

Manage Engineering Library: Efficient management of an engineering library involves organizing and accessing a wealth of design information. Data science plays a role in developing smart categorization and retrieval systems, ensuring quick access to relevant information, and optimizing the utilization of engineering resources.

Develop Electric Design Solution: Creating electric design solutions involves intricate planning and optimization. Data science can contribute by analyzing design parameters, historical electric design data, and performance metrics to suggest optimal solutions, ultimately improving the quality and efficiency of electric design.

Develop Functional Design: The development of functional design involves conceptualizing the purpose and operation of automation systems. Data science assists in this by analyzing functional requirements, historical design data, and user feedback to optimize the functional design process.

Develop Automation Design Solution: Like electric design, developing automation design solutions benefits from data science. By analyzing historical data, usage patterns, and system requirements, data science contributes to the creation of efficient and effective automation solutions.

Manage Automation and Electrical Objects: Data science aids in managing automation and electrical objects by implementing automated tagging, categorization, and retrieval systems. This ensures efficient organization, quick access, and seamless integration of these objects into the design process.

Develop Multidisciplinary System Design: Multidisciplinary system design involves integrating diverse design aspects seamlessly. Data science plays a role by analyzing the interdependencies between different disciplines, suggesting optimization strategies, and ensuring a cohesive system design.

Develop Safety System Design: Safety system design necessitates a meticulous approach to risk assessment and mitigation. Data science contributes by analyzing historical safety data, identifying potential risks, and optimizing safety system designs for enhanced reliability.

Manage Automation Design Environment: The efficient management of the automation design environment involves optimizing tools, interfaces, and collaboration platforms. Data science aids in this by analyzing user interactions, identifying usage patterns, and recommending improvements for an enhanced design environment.

Exchange Control Design Data with Partners: Effective collaboration requires seamless exchange of control design data with partners. Data science can optimize this process by developing intelligent data exchange protocols, ensuring data integrity, and streamlining communication channels.

Validate and Release Design Results: Validation and release of design results involve rigorous testing and compliance checks. Data science can expedite this process by implementing automated validation routines, predicting potential issues, and ensuring that design results adhere to specified standards.

In conclusion, the Collaborative Automation Design for Manufacturing Machine function encompasses a broad spectrum of activities vital for efficient design processes. The infusion of data science optimizes these activities by enhancing planning, design efficiency, collaboration, and decision-making. Additionally, by achieving business agility goals, data science contributes to a more adaptive, responsive, and inclusive design environment, ultimately fostering efficiency and innovation in manufacturing automation (Feng et al., 2009; Lu et al., 2017; Luo et al., 2021; Morinaga et al., 2006; Noel & Brissaud, 2003).

4.3.1.4 Machine Tool Automation Design

Within the domain of advanced manufacturing, the function of "Machine Tool Automation Design" holds a pivotal role in developing and optimizing automation solutions for machine tools. This multifaceted function encompasses activities shown in *Figure 178* such as developing Programmable Logic Controller (PLC) programs, parametrizing numerical control unit base software, validating drive topology, maintaining numerical control program archives, and validating and releasing automation design results.

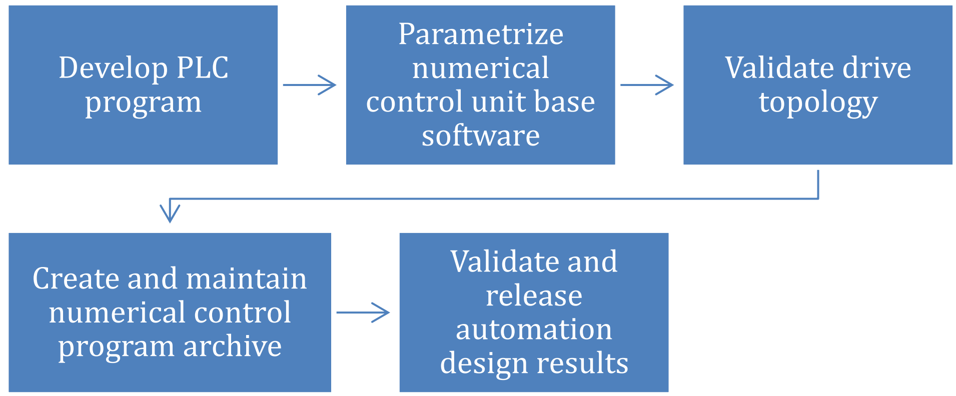

Figure 179 Typical Process Flow Machine Tool Automation Design.

Develop PLC Program: This activity involves creating the logic and functionality for the Programmable Logic Controller (PLC) that governs the automated processes of machine tools. Data science can enhance this process by analyzing historical PLC program performance data, identifying patterns, and optimizing code for improved efficiency and reliability.

Parametrize Numerical Control Unit Base Software: Parametrizing numerical control unit base software entails configuring the software parameters that dictate the operation of numerical control units. Data science can contribute by automating the parameter optimization process based on machine performance data, ensuring that parameters are finely tuned for optimal results.

Validate Drive Topology: Drive topology validation involves ensuring that the configuration of drives in the automation system aligns with design specifications. Data science can assist in this activity by analyzing drive performance data, predicting potential issues, and recommending adjustments to optimize the overall topology.

Create and Maintain Numerical Control Program Archive: This activity involves the creation and upkeep of an archive containing numerical control programs. Data science can enhance this process by implementing automated archival systems, utilizing version control algorithms, and predicting potential program conflicts or redundancies.

Validate and Release Automation Design Results: The final step involves validating and releasing the results of the automation design. Data science plays a vital role in this activity by analyzing design validation data, identifying potential discrepancies or errors, and providing insights to ensure that the released design meets the required standards.

In conclusion, the integration of data science into the Machine Tool Automation Design function optimizes activities such as PLC programming, numerical control unit software parametrization, drive topology validation, program archiving, and design result validation. By achieving business agility goals through improved behavioral and situational awareness, inclusive and augmented decision-making, as well as dynamic processes and resource management, this function becomes a strategic enabler for responsive and efficient operations in advanced manufacturing (Fuertjes et al., 2019; Liu et al., 2018; Nguyen et al., 2012; Park et al., 2018; Qin & Dong, 2020; Wang et al., 2018).

4.3.1.5 Machine Tool Electrical Design

The function of Machine Tool Electrical Design is a crucial component within the manufacturing domain, responsible for developing the electrical aspects of machine tools. This section explores key activities performed by this function as shown in *Figure 180*, including developing wiring schematics, sizing, and selecting motors and drives, creating drive topology, generating bills of material, and validating and releasing electrical design results. Additionally, the section delves into how data science can be applied to enhance each activity and subsequently discusses how achieving business agility goals can be facilitated through data science in this function.

Develop Wiring Schematics for Cabinet and CNC: This activity involves creating detailed wiring schematics for the electrical components within machine tool cabinets and CNC (Computer Numerical Control) systems. Data science can contribute by automating schematic generation through pattern recognition algorithms, reducing manual effort, and ensuring consistency in design.

Size and Select Motors and Drives: Sizing and selecting motors and drives is a critical task to ensure optimal performance. Data science can assist in this activity by analyzing historical data on machine tool performance, helping predict the ideal motor and drive specifications based on usage patterns, reducing the likelihood of over-sizing or under-sizing.

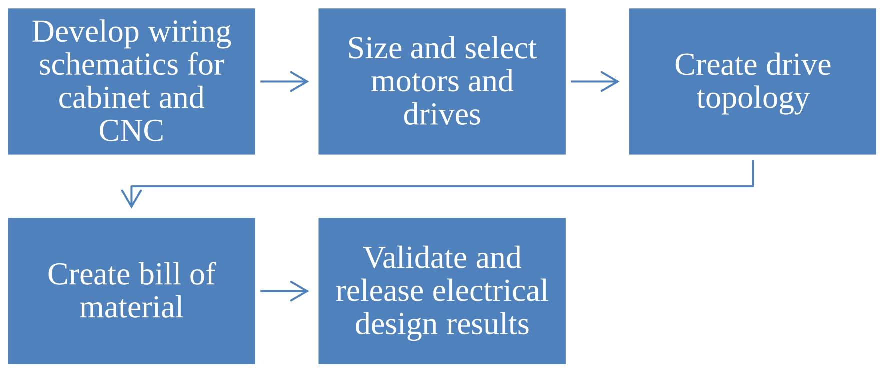

Figure 181 Typical Process Flow Machine Tool Electrical Design. Source: Author

Create Drive Topology: Creating drive topology involves designing the layout and interconnections of various drives within the machine tool. Data science applications, such as simulation models, can optimize drive topology by considering factors like efficiency, heat dissipation, and load distribution.

Create Bill of Material: Generating a comprehensive bill of material (BOM) is essential for procurement and assembly. Data science can automate the BOM creation process by integrating with product databases, ensuring accuracy, and facilitating real-time updates based on design changes.

Validate and Release Electrical Design Results: Validation of electrical design results ensures adherence to specifications and standards. Data science contributes by implementing validation algorithms that analyze design outputs, identifying potential errors or deviations, and supporting a more reliable and error-free release process.

In conclusion, the Machine Tool Electrical Design function is integral to manufacturing, and data science applications can significantly enhance its activities. From automating schematic generation to optimizing drive topology and achieving business agility goals, the integration of data science ensures efficiency, accuracy, and adaptability in the dynamic landscape of electrical design for machine tools (Gittler et al., 2019; Holsten et al., 2019; Jiang et al., 2019; Kang et al., 2020; Madhavi & Satyanarayana, 2022; Tüchsen et al., 2018).

4.3.1.6 Mitigation Strategies for Challenges in Adoption of Data Science

Table 31 outlines the Data Science use cases, business agility goals, challenges, risks, and mitigation strategies for each process in Manufacturing Systems Design.

Table 31 Data Science Use Cases for the various process in Manufacturing Systems Design function. Source: Author

Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
Manufacturing Line Design	Predictive modeling for layout optimization, Simulation-based validation	1. Lack of skilled workforce 2. Data quality and availability 3. Integration with existing systems	1. Project delays and increased costs 2. Inaccurate decision-making 3. Inefficient processes	1. Invest in training programs 2. Implement data quality checks 3. Collaborate with IT for seamless integration
Collaborative Automation Design for Manufacturing Line	Predictive modeling for automation design, Simulation-	1. Integration with existing systems 2. Lack of standardization	1. Data breaches and leaks 2. Inefficient processes	1. Implement robust data security measures 2. Establish

Table 31 Data Science Use Cases for the various process in Manufacturing Systems Design function. Source: Author				
Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
	based validation	3. Privacy and security concerns	3. System incompatibility	standardized protocols 3. Collaborate with IT for seamless integration
Collaborative Automation Design for Manufacturing Machine	Predictive modeling for automation design, Simulation-based validation	1. Integration with existing systems 2. Lack of standardization 3. Privacy and security concerns	1. Data breaches and leaks 2. Inefficient processes 3. System incompatibility	1. Implement robust data security measures 2. Establish standardized protocols 3. Collaborate with IT for seamless integration
Machine Tool Automation Design	Predictive maintenance, Predictive modeling for automation design	1. Lack of skilled workforce 2. Data quality and availability 3. Integration with existing systems	1. Equipment breakdowns and downtime 2. Inaccurate decision-making 3. Inefficient processes	1. Invest in training programs 2. Implement data quality checks 3. Collaborate with IT for seamless integration

Table 31 Data Science Use Cases for the various process in Manufacturing Systems Design function. Source: Author				
Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
Machine Tool Electrical Design	Predictive maintenance, Predictive modeling for electrical design	1. Data quality and availability 2. Integration with existing systems 3. Lack of standardization	1. Inaccurate decision-making 2. Inefficient processes 3. System incompatibility	1. Implement data quality checks 2. Collaborate with IT for seamless integration 3. Establish standardized protocols

Table 31 also highlights how data science can enhance various processes in Manufacturing Systems Design, contributing to business agility goals. However, organizations may face challenges such as lack of skilled workforce, data quality issues, integration complexities, and privacy concerns. Mitigation strategies include investing in training, implementing data quality checks, collaborating with IT, and establishing standardized protocols to ensure successful implementation of data science solutions.

4.3.2 Mitigation Strategies for Challenges in Adoption of Data Science in Automation Engineering and commissioning

Within the domain of Manufacturing Systems Design, a multitude of sub-functions collectively contribute to the smooth and efficient operation of manufacturing processes. These sub-functions encompass diverse activities, each playing a pivotal role in ensuring the overall efficacy of the manufacturing system. The integration of data science into these sub-functions holds substantial promise for enhancing capabilities and optimizing outcomes. This section provides a detailed overview of the sub-functions as shown in *Figure 182* inherent to Manufacturing Systems Design.

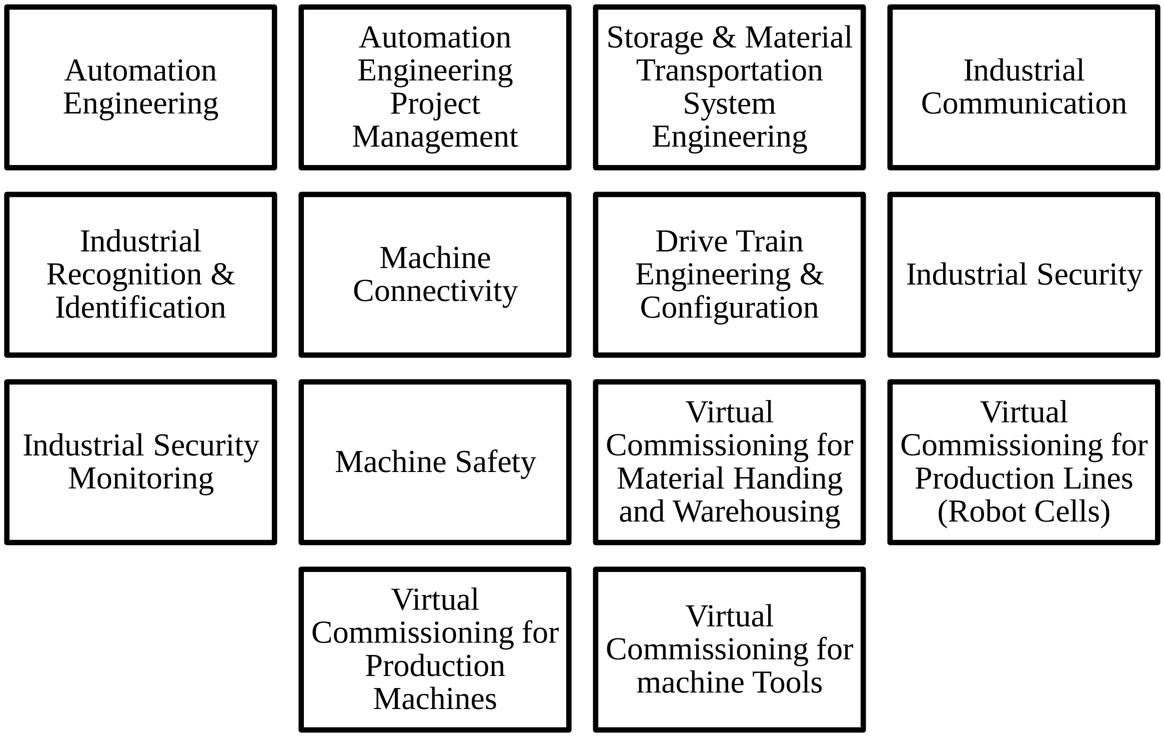

Figure 183 Sub functions in Automation Engineering and commissioning. Source: Author

The infusion of data science into the various sub-functions of Manufacturing Systems Design opens new frontiers for innovation and efficiency. The symbiotic relationship between automation engineering, project management, material handling, and virtual commissioning, when coupled with data science, propels manufacturing operations towards a future characterized by adaptability, precision, and continuous improvement. As industries evolve, embracing the transformative power of data science becomes not just a competitive advantage but a fundamental prerequisite for staying at the forefront of the rapidly changing manufacturing landscape (Qin & Dong, 2020; Sajid et al., 2021; Shafiq et al., 2019; Vazan et al., 2017; Yu & Nielsen, 2020; Zadeh & Shahbazy, 2020).

4.3.2.1 Automation engineering

The Automation Engineering function plays a pivotal role in ensuring the efficient and streamlined operation of automated systems within a broader organizational context. This section explores the diverse activities encompassed by Automation Engineering as shown in *Figure 184* and delves into how data science can be integrated into each of these activities to enhance operational efficiency.

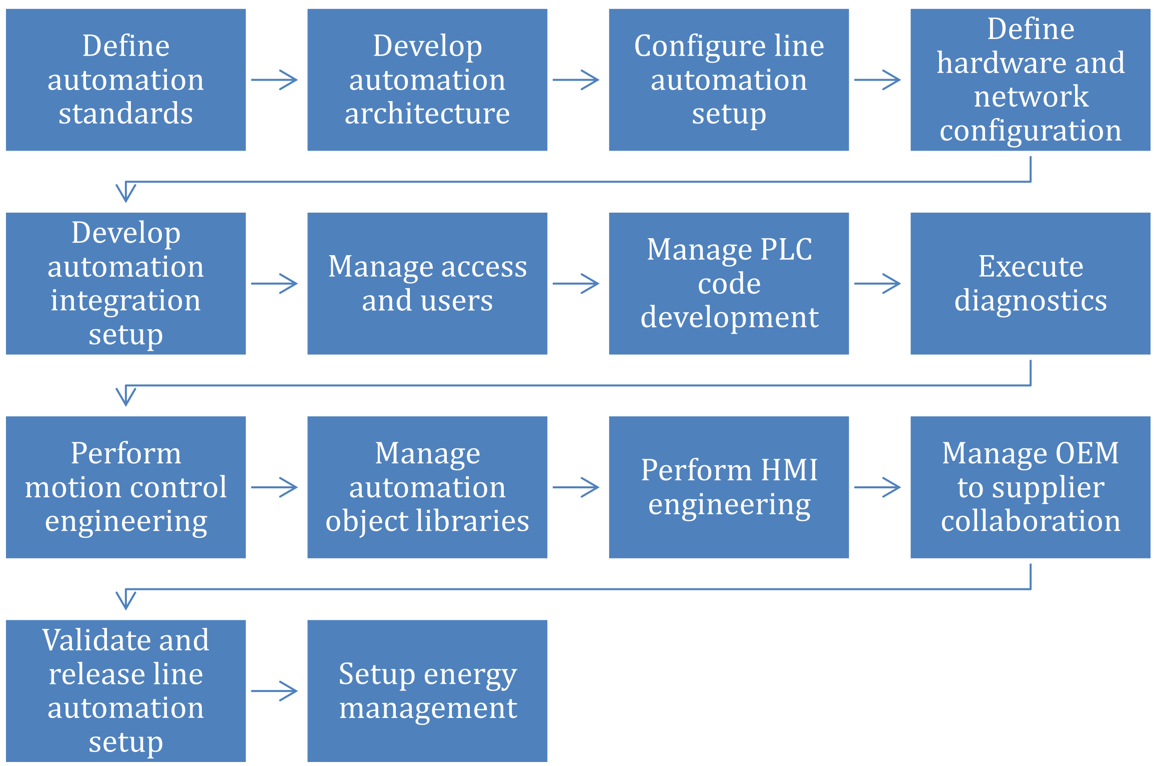

Figure 185 Typical Process Flow in Automation engineering. Source: Author

Define Automation Standards: This involves establishing standardized protocols and guidelines for automation processes. Data science can contribute by analyzing historical performance data to identify areas for standardization and optimizing standards based on evolving industry best practices.

Develop Automation Architecture: Automation architecture development entails designing the overall structure of automated systems. Data science can assist by utilizing predictive modeling to optimize architecture based on historical performance data, ensuring scalability and efficiency.

Configure Line Automation Setup: Configuring line automation setups involves tailoring systems to meet specific operational requirements. Data science can automate configuration processes, ensuring accuracy and efficiency by analyzing historical configuration data and identifying patterns.

Define Hardware and Network Configuration: This activity involves specifying the hardware components and network configurations required for automation systems. Data science contributes by analyzing performance data to recommend optimal configurations, improving system reliability and performance.

Develop Automation Integration Setup: Automation integration setup involves connecting various components of automated systems. Data science can streamline this process by analyzing integration data to identify potential bottlenecks, ensuring seamless communication between different modules.

Manage Access and Users: Managing access and user permissions ensures the security and controlled operation of automation systems. Data science can enhance access management by implementing predictive analytics to identify potential security threats and optimize user access based on historical usage patterns.

Manage PLC Code Development: This involves the creation and maintenance of Programmable Logic Controller (PLC) code. Data science can optimize code development by analyzing historical code performance, identifying areas for improvement, and automating certain coding tasks.

Execute Diagnostics: Diagnostics execution involves identifying and resolving issues within automated systems. Data science contributes by implementing predictive maintenance models, allowing for proactive issue resolution based on historical performance data.

Perform Motion Control Engineering: Motion control engineering involves managing and optimizing the movement of machinery. Data science can enhance motion control by analyzing real-time data to identify inefficiencies and optimize control strategies.

Manage Automation Object Libraries: Managing object libraries involves organizing and maintaining standardized automation objects. Data science can automate object library management by analyzing historical library usage data, ensuring consistency and efficiency.

Perform HMI Engineering: Human-Machine Interface (HMI) engineering involves designing interfaces for human interaction with automated systems. Data science can optimize HMI design by analyzing user interaction data, ensuring user-friendly and efficient interfaces.

Manage OEM to Supplier Collaboration: Collaboration between Original Equipment Manufacturers (OEMs) and suppliers is crucial. Data science can facilitate collaboration by analyzing communication patterns, optimizing collaboration workflows, and ensuring effective knowledge exchange.

Validate and Release Line Automation Setup: Validation and release activities ensure that automated systems meet specified standards. Data science contributes by implementing validation models that analyze system performance data, ensuring compliance and reliability before release.

Setup Energy Management: Energy management involves optimizing the use of energy resources within automation systems. Data science can enhance energy management by analyzing real-time energy consumption data, identifying inefficiencies, and optimizing energy usage patterns.

In summary, the Automation Engineering function encompasses a range of activities crucial for the effective operation of automated systems. Integrating data science into these activities enhances efficiency, accuracy, and adaptability. By leveraging AI tools, organizations can achieve business agility goals, including improving behavioral awareness, situational awareness, inclusive decision-making, augmented decision-making, dynamic processes, and dynamic resource allocation. This synergistic integration of data science and business agility goals contributes to a more responsive and efficient Automation Engineering (Coleman, 2019; Nasution, 2021; Qin & Dong, 2020; Sajid et al., 2021; Zucker et al., 2015).

4.3.2.2 Automation engineering project management

The function of Automation Engineering Project Management is a critical aspect within organizational operations, responsible for overseeing the initiation, management, and release of automation engineering projects. This section delves into the key activities performed within this function as shown in *Figure 186*, followed by an exploration of how data science can enhance these activities. Additionally, a separate section discusses how data science contributes to achieving various business agility goals within the context of this function.

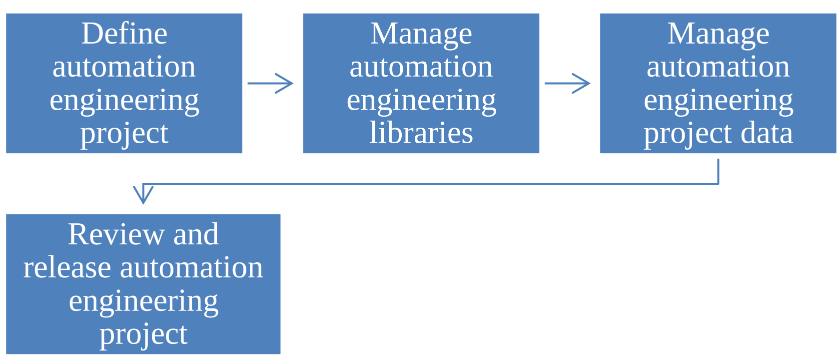

Figure 187 Process Flow in Automation engineering project management. Source: Author

Define Automation Engineering Project: This activity involves establishing the scope, objectives, and requirements of an automation engineering project. Data science can aid in this phase by utilizing predictive modeling to analyze historical project data, identifying patterns, and assisting in defining realistic project parameters and goals.

Manage Automation Engineering Libraries: Efficient library management is crucial for reusability and consistency in automation engineering projects. Data science, through automated data tagging and categorization, ensures that libraries are organized, searchable, and aligned with project needs, fostering efficiency, and reducing redundancy.

Manage Automation Engineering Project Data: This activity focuses on handling the vast amounts of data generated during an automation engineering project. Data science plays a pivotal role by implementing data analytics and machine learning algorithms to extract valuable insights, monitor progress, and identify potential issues in real-time.

Review and Release Automation Engineering Project: Before a project is released, it undergoes thorough review and validation processes. Data science contributes by automating review workflows, employing machine learning models to assess project quality, and ensuring compliance with predefined standards, leading to more efficient and reliable releases.

In summary, Automation Engineering Project Management involves defining project parameters, managing libraries and project data, and overseeing the review and release processes. Data science enhances these activities by providing predictive insights, automating workflows, and ensuring data-driven decision-making. Furthermore, data science contributes to achieving business agility goals within this function, fostering behavioral awareness, situational awareness, inclusive decision-making, augmented decision-making, and the creation of dynamic processes and resources for fast execution (Grabis et al., 2019; Haidabrus et al., 2021; Kutzias & Dukino, 2022; Qin & Dong, 2020; Wang, 2021).

4.3.2.3 Storage and material transportation system engineering

The function responsible for "Storage and Material Transportation System Engineering" plays a critical role in the optimization and automation of storage and transportation processes as shown in *Figure 188*. This section explores the key activities within this function, including developing transportation and storage automation concepts, configuring conveyor and storage system setups, simulating, and optimizing system configurations, and validating and releasing automation setups.

Develop Transportation System Automation Concept: This activity involves conceptualizing and designing automated transportation systems. Data science contributes by analyzing historical transportation data to identify patterns, predict optimal routes, and optimize system designs. Predictive modeling can enhance the efficiency of transportation concepts.

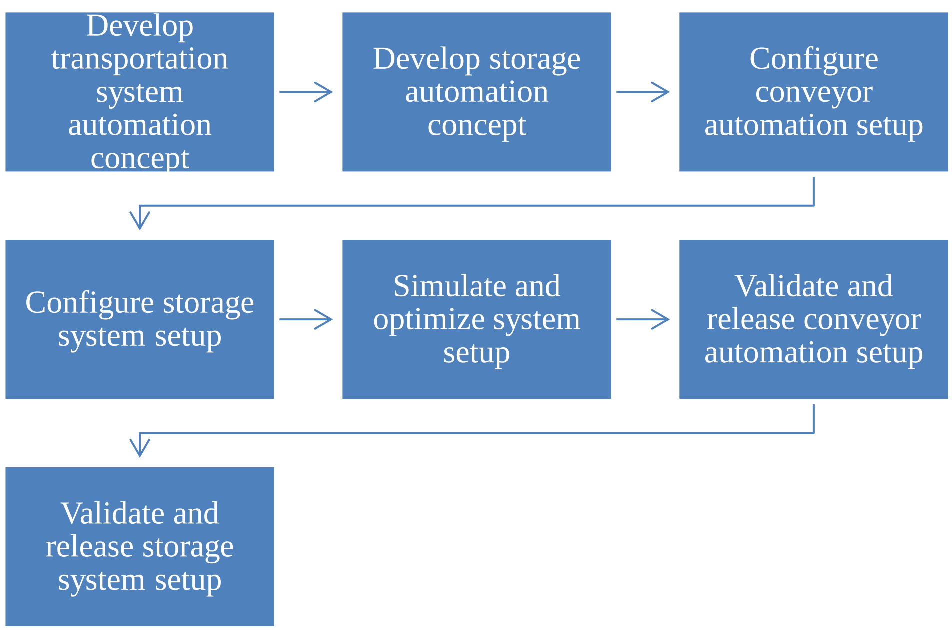

Figure 189 Storage and material transportation system engineering. Source: Author

Develop Storage Automation Concept: Like transportation, data science aids in developing storage automation concepts. Analyzing historical storage data helps identify storage patterns, predict space utilization, and optimize automated storage designs. This ensures efficient and space-effective storage automation.

Configure Conveyor Automation Setup: Data science supports configuring conveyor automation setups by leveraging machine learning algorithms to optimize conveyor configurations. Real-time data analysis can adapt conveyor setups based on dynamic factors such as varying workloads or changing product types, ensuring flexibility and efficiency.

Configure Storage System Setup: Configuring storage system setups is enhanced by data science through automated algorithms that optimize storage configurations. Predictive modeling can anticipate storage needs, ensuring that the setup aligns with the dynamic demands of the materials being stored.

Simulate and Optimize System Setup: This activity involves simulating the entire storage and transportation system to identify potential bottlenecks and areas for improvement. Data science contributes by running simulations based on historical and real-time data, enabling optimization of the entire system for efficiency and throughput.

Validate and Release Conveyor Automation Setup: Data science ensures the validation and release of conveyor automation setups by analyzing performance data. Predictive analytics can identify potential issues, validate the setup against predefined criteria, and release the configuration for operational use.

Validate and Release Storage System Setup: Like conveyor setups, data science validates and releases storage system setups. Predictive modeling can assess the setup's compliance with storage requirements, ensuring that the released configuration aligns with the dynamic storage needs of the organization.

In summary, the "Storage and Material Transportation System Engineering" function encompasses activities that are crucial for efficient logistics and material management.

Integrating data science enhances the development, configuration, simulation, and validation of automation setups. Additionally, leveraging data science for business agility goals contributes to improved behavioral and situational awareness, inclusive and augmented decision-making, and the creation of dynamic processes and resources for fast execution within this function (Arantes et al., 2018; Fox, 2018; Kibira et al., 2015; Qin & Dong, 2020; Sajid et al., 2021).

4.3.2.4 Industrial communication

Within the realm of industrial communication, a multifaceted function encompasses various activities critical to the efficiency and reliability of communication networks. This section explores the activities performed by this function as shown in *Figure 190*, which include planning and setting up networks, integrating data security concepts, simulating, and optimizing performance, diagnosing issues, testing networks, and managing and monitoring performance. Additionally, it delves into how data science can enhance each activity.

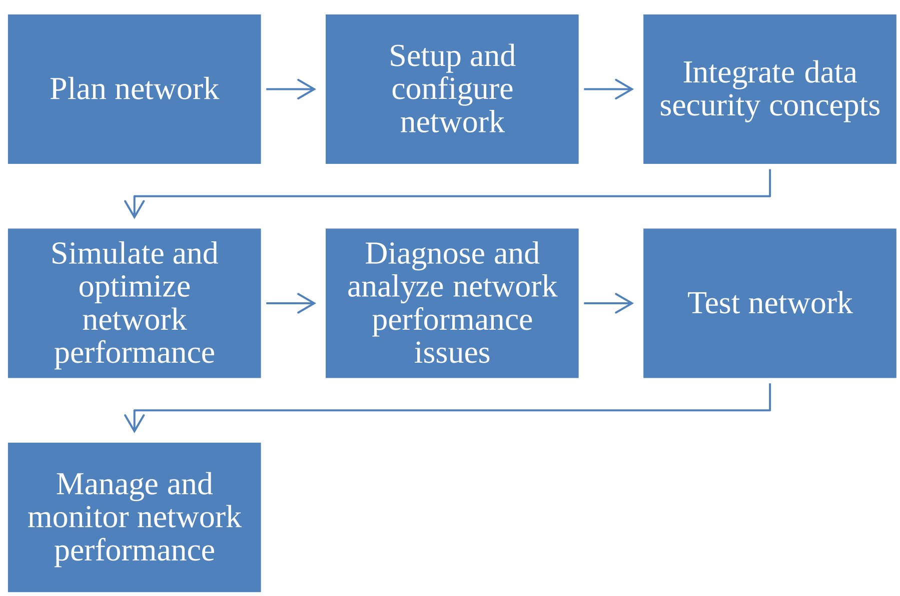

Figure 191 Typical Process flow in Industrial communication Engineering. Source: Author

Plan Network: The planning phase involves designing a robust communication network. Data science contributes by analyzing historical data, predicting traffic patterns, and optimizing network architectures to ensure efficient communication and resource utilization.

Setup and Configure Network: Data science aids in the setup and configuration by automating the deployment process. Machine learning algorithms can analyze network requirements, adapting configurations dynamically to meet specific needs, thereby streamlining the setup process.

Integrate Data Security Concepts: Data science reinforces data security by employing advanced analytics to detect anomalies, identify potential security threats, and predict vulnerabilities. This proactive approach enhances the integration of robust data security concepts within the communication network.

Simulate and Optimize Network Performance: Simulation and optimization benefit from data science through predictive modeling. By analyzing historical performance data and simulating different scenarios, machine learning models can optimize network parameters for enhanced efficiency and responsiveness.

Diagnose and Analyze Network Performance Issues: Data science plays a crucial role in diagnosing issues by implementing real-time analytics. Predictive models can identify performance anomalies, allowing for proactive issue resolution and minimizing downtime in the communication network.

Test Network: Data-driven testing involves leveraging analytics to design comprehensive test scenarios. Machine learning algorithms can predict potential failure points, ensuring thorough testing and validation of the communication network.

Manage and Monitor Network Performance: Data science enhances performance management and monitoring through real-time analytics. Predictive models can anticipate potential bottlenecks, enabling proactive management to maintain optimal network performance.

In summary, the function responsible for industrial communication encompasses activities vital for network efficiency. Data science enhances each activity by providing predictive modeling, real-time analytics, and automation, contributing to improved planning, security, optimization, and management of communication networks. Furthermore, data science significantly contributes to achieving business agility goals by fostering awareness, enabling informed decision-making, and creating dynamic processes and resources for swift execution (Amin et al., 2021; Atov et al., 2019; Coleman, 2019; Foroughi & Luksch, 2018; Izenman, 2023; Jiang et al., 2019).

4.3.2.5 Industrial recognition and identification

The function responsible for "Industrial Recognition and Identification" plays a crucial role in managing identification systems within industrial settings.

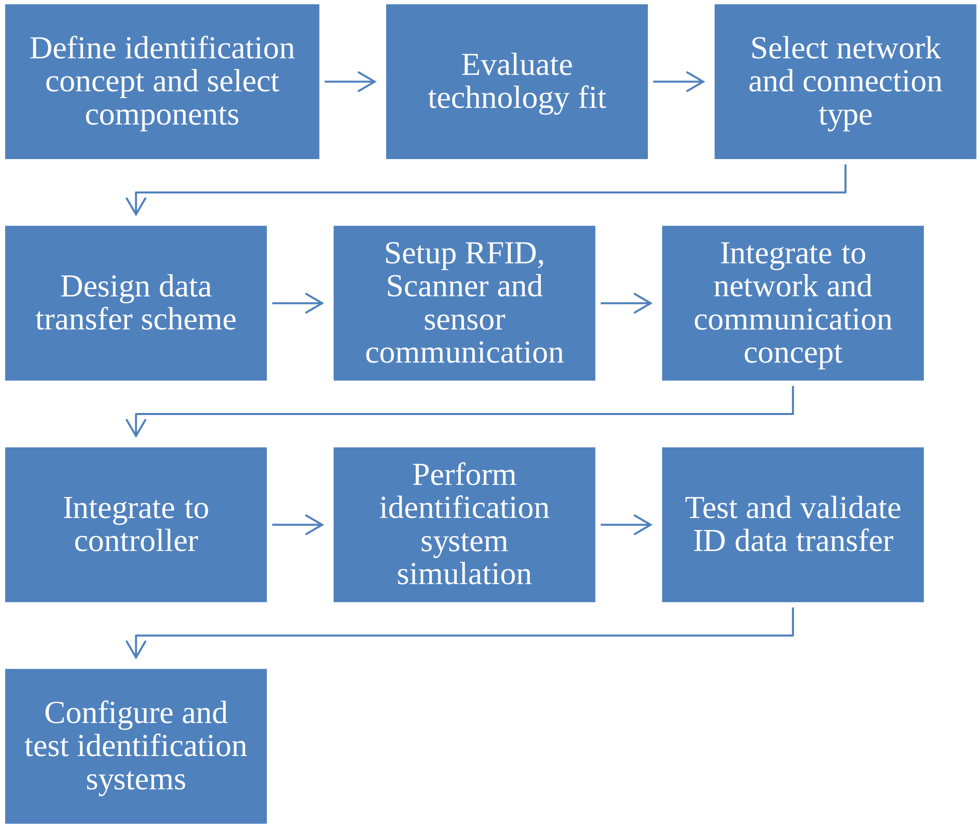

Figure 192 Typical Process Flow Industrial recognition and identification Engineering. Source: Author

As shown in *Figure 193***,** this encompasses activities such as defining identification concepts, selecting components, evaluating technology fit, designing data transfer schemes, and testing and validating identification systems. Leveraging data science in this function introduces efficiency and accuracy, optimizing identification processes and contributing to overall business agility.

Define Identification Concept and Select Components: This activity involves conceptualizing the identification system and selecting appropriate components. Data science can aid in this by analyzing historical data to identify trends and requirements, ensuring the selection of components aligns with the specific needs of the industrial context.

Evaluate Technology Fit: The evaluation of technology fit involves assessing the compatibility of chosen technologies with the identified requirements. Data science contributes by conducting comparative analyses, considering factors such as performance, scalability, and historical success rates to determine the optimal technology fit.

Select Network and Connection Type: The selection of network and connection types involves choosing communication protocols. Data science can assist by analyzing data transfer requirements and network performance metrics, ensuring the chosen types align with efficiency and reliability needs.

Design Data Transfer Scheme: Data science can optimize the design of data transfer schemes by predicting data transfer patterns, analyzing potential bottlenecks, and recommending efficient schemes based on historical data and performance trends.

Setup RFID, Scanner, and Sensor Communication: This activity involves configuring communication channels for RFID, scanners, and sensors. Data science contributes by automating configuration processes, ensuring seamless communication, and leveraging predictive analytics to anticipate communication challenges.

Integrate to Network and Communication Concept: Data science aids in the integration of identification systems into network and communication concepts by automating integration processes and optimizing network configurations based on real-time data and performance analytics.

Integrate to Controller: Integration with controllers involves ensuring seamless coordination between identification systems and controllers. Data science can contribute by automating integration processes, analyzing controller performance, and predicting potential integration challenges.

Perform Identification System Simulation: Simulation activities can be optimized using data science by developing realistic simulation models based on historical data, ensuring accurate representation of real-world scenarios, and facilitating effective testing.

Test and Validate ID Data Transfer: Data science-driven analytics can enhance the testing and validation process by automating test scenarios, analyzing real-time data transfer, and predicting potential issues, ensuring robust validation of ID data transfer systems.

Configure and Test Identification Systems: Configuration and testing activities benefit from data science by automating configuration processes, predicting testing scenarios based on historical data, and optimizing testing procedures for efficient and accurate outcomes.

In summary, integrating data science into the Industrial Recognition and Identification function optimizes various activities involved in identification system management. From conceptualization to testing and validation, data science enhances efficiency and accuracy. Moreover, by achieving specific business agility goals, such as improving awareness and enabling augmented decision-making, organizations can foster adaptability and responsiveness within their industrial processes. This data-centric approach ensures a more agile and effective Industrial Recognition and Identification function within the broader context of supply chain collaboration and material management (Ljung et al., 2011; Pane et al., 2018; Raptis et al., 2019; Yi, 2014).

4.3.2.6 Machine connectivity

Within the framework of Machine Connectivity, this function encompasses a series of activities crucial for establishing seamless connections with IoT devices and optimizing data provision configurations. As shown in *Figure 194*, the activities include analyzing capabilities for machine connectivity, defining data provision configurations, connecting to IoT devices, configuring standard machine interfaces, and enabling machines for data provision.

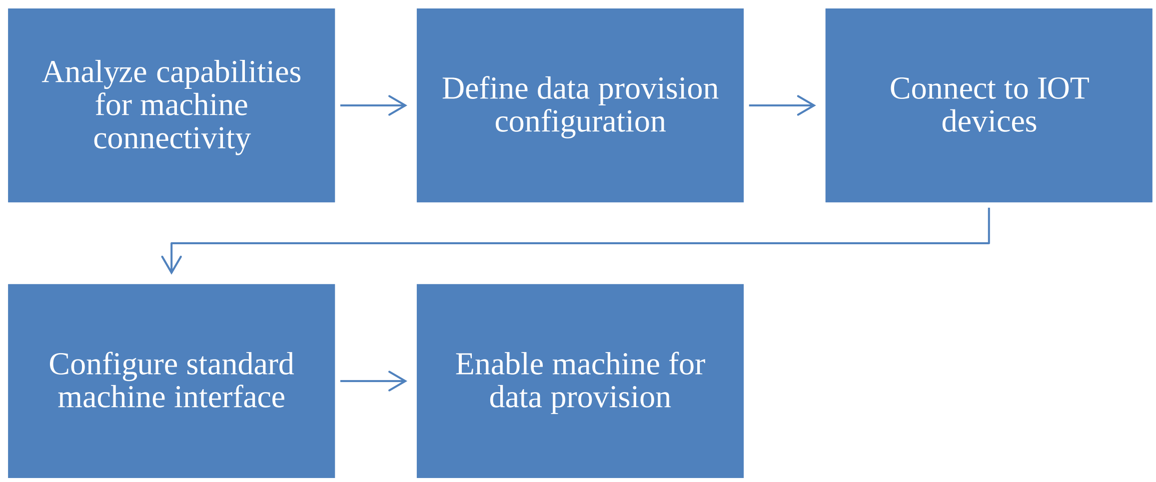

Figure 195 Process Flow in Machine connectivity Engineering. Source: Author

Analyzing Capabilities for Machine Connectivity: This involves assessing the technical capabilities of machines to establish connectivity. Data science can contribute by analyzing machine data, assessing compatibility, and predicting potential connectivity challenges. Predictive analytics can identify optimal connectivity solutions based on historical data and machine capabilities.

Defining Data Provision Configuration: Data provision configurations need to be meticulously defined to ensure efficient data transfer between machines and systems. Data science aids in optimizing these configurations by analyzing data flow patterns, identifying bottlenecks, and recommending configuration adjustments to enhance data provision efficiency.

Connecting to IoT Devices: Establishing connections to IoT devices involves leveraging data science to analyze device compatibility and communication protocols. Machine learning algorithms can be applied to identify the most effective methods for connecting to diverse IoT devices, ensuring seamless integration into the connectivity framework.

Configuring Standard Machine Interface: Standard machine interfaces play a pivotal role in achieving uniformity and compatibility across machines. Data science contributes by analyzing various machine interfaces, identifying commonalities, and recommending standardized configurations. This ensures a consistent and interoperable machine connectivity infrastructure.

Enable Machine for Data Provision: Enabling machines for data provision involves configuring devices to actively participate in data sharing processes. Data science plays a role by analyzing machine capabilities, predicting optimal data provision strategies, and automating the configuration processes to expedite the readiness of machines for data provision.

In summary, the function of Machine Connectivity involves activities ranging from analyzing capabilities and configuring interfaces to enabling machines for data provision. Data science plays a pivotal role by optimizing these activities through predictive analytics, machine learning, and AI-driven insights. Moreover, data science significantly contributes to enhancing business agility by improving behavioral awareness, situational awareness, inclusive decision-making, augmented decision-making, and facilitating dynamic processes and resources for swift execution within the realm of machine connectivity (Manikandan et al., 2022; Basheer et al., 2019; Ranjan et al., 2018; Sarigiannidis et al., 2017; Sudarmani et al., 2022; Verdugo Cedeño et al., 2018).

4.3.2.7 Drive train engineering and configuration

The function responsible for "Drive Train Engineering and Configuration" encompasses a range of activities as shown in *Figure 196* are critical to the development and optimization of drive train systems. This section delves into the various activities conducted within this function and explores the ways in which data science can be applied to enhance efficiency, decision-making, and overall business agility.

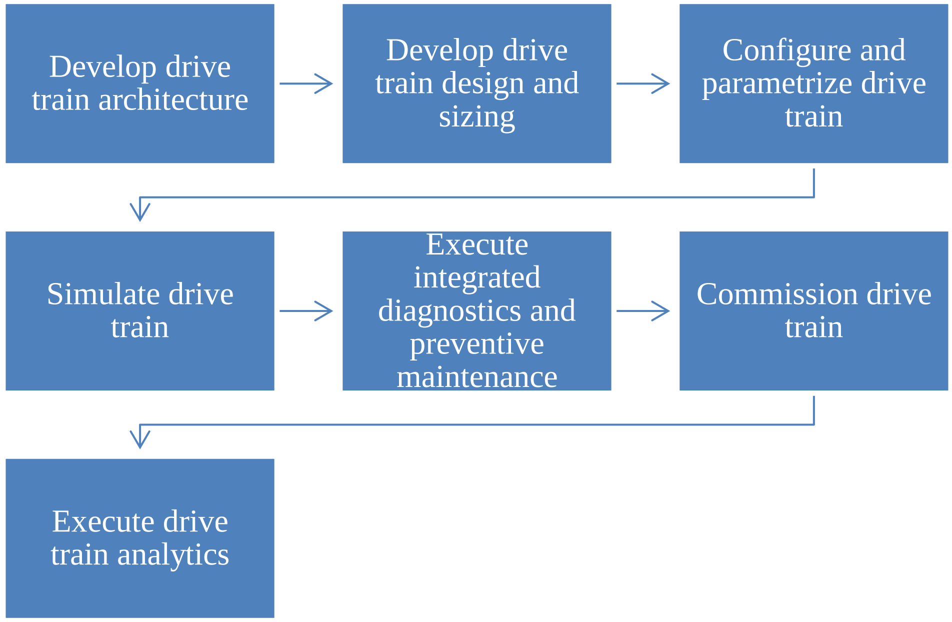

Figure 197 Typical Process Flow in Drive train engineering and configuration. Source : Author

Develop Drive Train Architecture: This activity involves conceptualizing and defining the overall structure and layout of the drive train system. Data science can contribute by analyzing historical drive train data, market trends, and performance metrics to inform the development of optimal architectures, ensuring efficiency and effectiveness.

Develop Drive Train Design and Sizing: This activity focuses on the detailed design and sizing of individual components within the drive train. Data science techniques, such as machine learning algorithms, can analyze historical design data, performance requirements, and material specifications to optimize the design and sizing process.

Configure and Parametrize Drive Train: Configuration and parameterization involve setting up the drive train system according to specific requirements. Data science aids in this activity by automating the configuration process based on historical configurations, real-time conditions, and evolving performance metrics.

Simulate Drive Train: Simulation is crucial for testing and validating the drive train's performance under various conditions. Data science-driven simulations use predictive analytics to model real-world scenarios, providing insights into potential issues and optimizing the drive train's performance.

Execute Integrated Diagnostics and Preventive Maintenance: This activity involves implementing diagnostic systems to monitor drive train health and conducting preventive maintenance to avoid failures. Data science can enhance this process by utilizing machine learning for predictive maintenance, analyzing sensor data to anticipate issues and optimize maintenance schedules.

Commission Drive Train: Commissioning involves the initial setup and testing of the drive train in its operational environment. Data science contributes by automating commissioning processes, analyzing real-time data during commissioning, and ensuring a smooth integration into the broader system.

Execute Drive Train Analytics: Drive train analytics involves continuous monitoring, analysis, and optimization of performance. Data science enables real-time analytics by processing vast amounts of data from sensors and other sources, providing actionable insights for ongoing improvements in drive train efficiency.

In summary, the "Drive Train Engineering and Configuration" function involves a series of activities crucial to the development and optimization of drive train systems. By integrating data science into these activities, the function can achieve improved efficiency, decision-making, and overall business agility. From optimizing design and sizing to implementing preventive maintenance and enabling inclusive decision-making, data science plays a transformative role in enhancing the agility and effectiveness of the drive train engineering function (Hiruta et al., 2019; Kibira et al., 2015; Rasool & Chaudhary, 2022; Qin & Dong, 2020; Sajid et al., 2021).

4.3.2.8 Industrial network security

Within the broader landscape of industrial operations, the function responsible for "Industrial Network Security" assumes a pivotal role in safeguarding critical assets and information. This section explores key activities performed by this function as shown in *Figure 198*, including installing and managing know-how and copy protection, managing authentication and users, installing firewall and VPN, and performing system hardening and analytics.

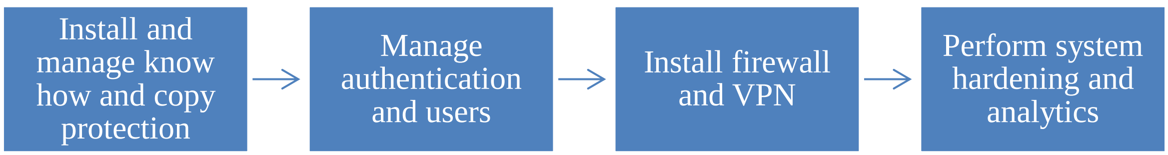

Figure 199 Typical Process for Industrial network security engineering. Source : Author

Install and Manage Know-How and Copy Protection: This involves implementing mechanisms to protect intellectual property and sensitive information. Data science can be employed to detect anomalies in data access patterns, identifying potential unauthorized attempts. Machine learning algorithms can learn from historical data to predict and prevent unauthorized copying or access to critical know-how.

Manage Authentication and Users: Ensuring secure user access through robust authentication methods. Data science contributes by implementing adaptive authentication models that analyze user behavior, detect anomalies, and adjust authentication requirements dynamically. This enhances security by recognizing and responding to evolving user patterns.

Install Firewall and VPN: Implementing firewalls and Virtual Private Networks (VPNs) to secure network communication. Data science enhances these measures by leveraging predictive analytics to identify potential security threats, adapting firewall rules dynamically based on emerging patterns. Machine learning models can optimize VPN performance and security based on historical usage data.

Perform System Hardening and Analytics: Strengthening system security by removing unnecessary functionalities and vulnerabilities. Data science supports system hardening by continuously analyzing system logs and data points for potential vulnerabilities. Machine learning models can predict and proactively address system weaknesses, enhancing overall security resilience.

The function of Industrial Network Security encompasses critical activities to secure industrial operations. The integration of data science enhances these activities by providing predictive capabilities, adaptive security measures, and continuous analytics. Moreover, leveraging data science for business agility goals such as improving behavioral awareness, situational awareness, inclusive decision-making, augmented decision-making, dynamic processes, and dynamic resources ensures a robust and adaptive security framework within industrial networks (Bhrugubanda & Prasuna, 2021; Foroughi & Luksch, 2018; Lin et al., 2020; Sarker, 2020; Tewari, 2021; Yan et al., 2021).

4.3.2.9 Industrial network security monitoring

The function of Industrial Network Security Monitoring is crucial in safeguarding industrial networks from potential threats and vulnerabilities. This section explores the key activities within this function as shown in *Figure 200*, including connecting and configuring security setups, monitoring data and networks, managing alerts, and defining security measures. Additionally, it delves into how data science can be harnessed to enhance each activity. Following this, a separate section discusses how data science can contribute to achieving various business agility goals in the context of Industrial Network Security Monitoring.

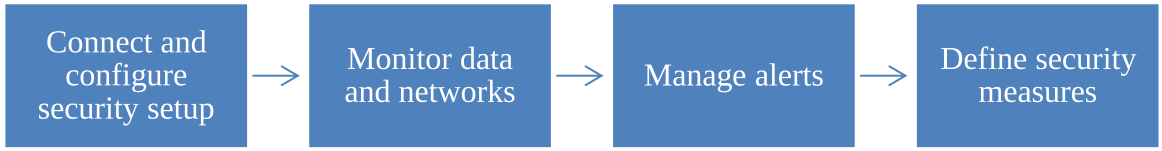

Figure 201 Typical Process in Industrial network security monitoring. Source: Author

Connect and Configure Security Setup: This activity involves establishing and configuring the security infrastructure for industrial networks. Data science can assist in this by analyzing historical security data to identify optimal configurations. Machine learning algorithms can recommend setup parameters based on evolving threat landscapes and network patterns.

Monitor Data and Networks: Monitoring data and networks in real-time is essential for identifying anomalies and potential security breaches. Data science contributes by employing anomaly detection algorithms to analyze network traffic and data patterns, enabling the swift identification of unusual activities that may indicate security threats.

Manage Alerts: Efficient alert management involves prioritizing and responding to security alerts promptly. Data science enhances this process by implementing predictive analytics models. These models assess the severity of alerts, prioritize them based on historical threat data, and recommend appropriate response actions.

Define Security Measures: Defining robust security measures requires a comprehensive understanding of emerging threats and vulnerabilities. Data science facilitates this by continuously analyzing threat intelligence data, identifying new patterns, and recommending proactive security measures to address evolving risks.

In summary, Industrial Network Security Monitoring, supported by data science, plays a vital role in securing industrial networks. By connecting and configuring security setups, monitoring data and networks, managing alerts, and defining security measures, this function establishes a robust security framework. Furthermore, data science contributes to business agility goals by improving behavioral and situational awareness, enabling inclusive and augmented decision-making, and creating dynamic processes and resources for fast execution in response to evolving security challenges (Anton et al., 2019; Francia, 2017; Lin & Liu, 2019; Lin et al., 2020; Qiao et al., 2020; Yu et al., 2021; Zhang et al., 2020).

4.3.2.10 Machine Safety

The function responsible for "Machine Safety" encompasses critical activities aimed at ensuring the secure and reliable operation of machines. This section delves into the activities performed within this function, highlighting the importance of data security, machine safety verification, safety concept definition, safety setup configuration, and safety validation execution. Additionally, the integration of data science is explored to enhance each activity and subsequently improve business agility goals.

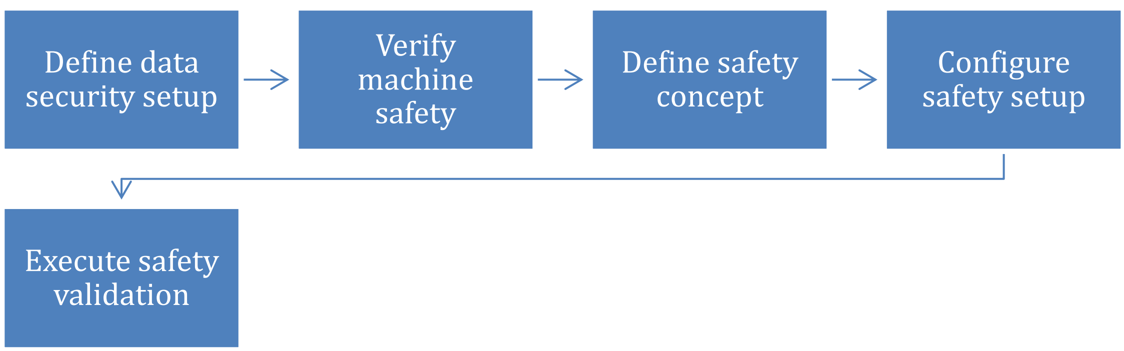

Figure 202 Typical Process in Machine Safety during automation engineering. Source: Author

Define Data Security Setup: This activity involves establishing a robust data security framework for machine safety systems. Data science contributes by implementing advanced encryption algorithms, anomaly detection models, and access control mechanisms. Utilizing data science ensures the confidentiality and integrity of machine safety data, safeguarding against potential cyber threats.

Verify Machine Safety: Verification is a crucial step to ensure that machine safety measures meet predefined standards. Data science can enhance this process by employing predictive modeling and simulation. By analyzing historical safety data, machine learning models can predict potential safety issues, enabling proactive adjustments to prevent incidents.

Define Safety Concept: Defining the safety concept involves outlining the overall strategy for ensuring machine safety. Data science plays a role by analyzing past safety incidents and near-misses to identify patterns and trends. This analysis informs the development of comprehensive safety concepts that address potential risks and enhance overall safety strategies.

Configure Safety Setup: Configuration of safety setups involves tailoring safety parameters to specific machine requirements. Data science contributes by automating configuration processes through machine learning algorithms that analyze machine behavior and adapt safety settings dynamically. This ensures that safety configurations align with real-time operational conditions.

Execute Safety Validation: Safety validation execution is the practical assessment of implemented safety measures. Data science enhances this activity by implementing real-time monitoring using AI-driven analytics. By continuously analyzing safety data, machine learning models can identify anomalies or deviations from expected safety behavior, enabling swift corrective actions.

In conclusion, the function of "Machine Safety" involves defining data security setups, verifying machine safety, defining safety concepts, configuring safety setups, and executing safety validation. Integrating data science enhances each activity, contributing to improved behavioral awareness, situational awareness, inclusive decision-making, augmented decision-making, and the creation of dynamic processes and resources for fast execution. This integration ensures a proactive, adaptive, and efficient approach to machine safety within the broader context of supply chain collaboration and material management (Bhrugubanda & Prasuna, 2021; Faulkner & Nicholson, 2020; Foroughi & Luksch, 2018; Nesan et al., 2022; Sarker, 2020).

4.3.2.11 Virtual commissioning of material handling and warehousing system

The function responsible for the virtual commissioning of material handling and warehousing systems is pivotal in the development, testing, and optimization of conveying systems. This section explores the key activities performed by this function as shown in Figure 203 and delves into how data science can enhance each activity. Additionally, it discusses how the integration of data science contributes to achieving various business agility goals.

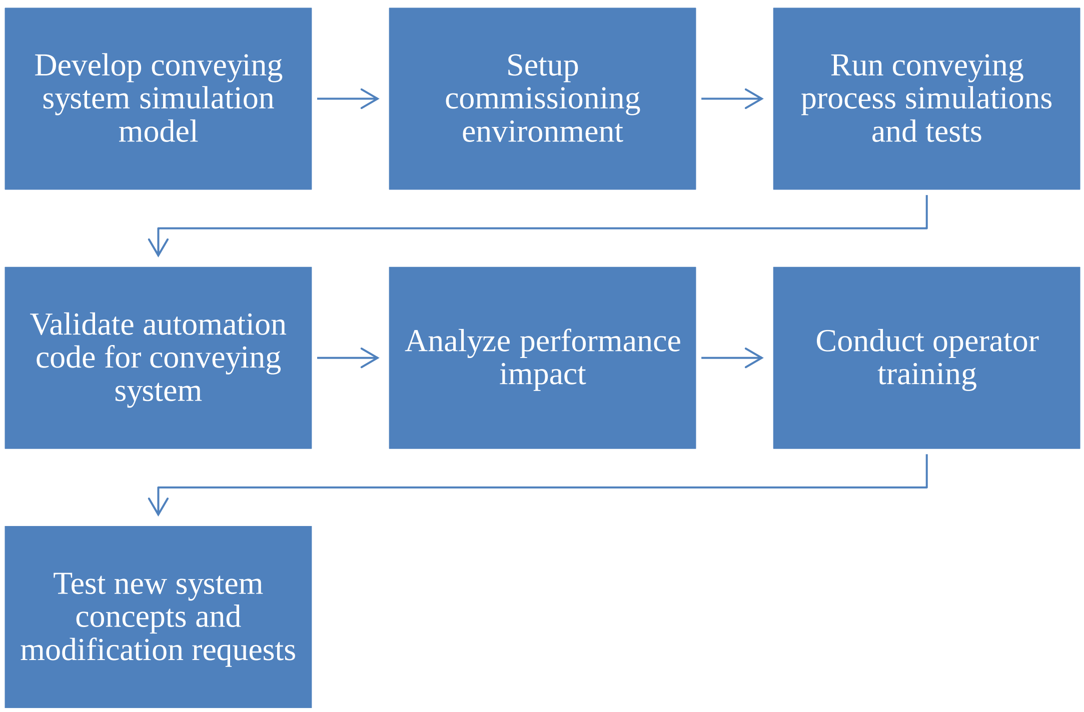

Figure 204 Typical Virtual commissioning of material handling and warehousing system. Source: Author

Develop Conveying System Simulation Model: This activity involves creating a detailed simulation model of the conveying system. Data science contributes by analyzing historical data, production patterns, and system dynamics to build accurate and realistic simulation models. Machine learning algorithms can optimize simulation based on historical performance data, ensuring the model's effectiveness.

Setup Commissioning Environment: Data science aids in configuring the commissioning environment by analyzing environmental factors, system specifications, and historical data. Predictive analytics can optimize the setup process, considering factors like resource availability and system requirements.

Run Conveying Process Simulations and Tests: Data science plays a crucial role in running simulations and tests by providing real-time data analytics. Machine learning models can predict potential issues during simulations, allowing for proactive adjustments and ensuring the reliability of the testing phase.

Validate Automation Code for Conveying System: Validation of automation code benefits from data science through automated code analysis. Machine learning algorithms can identify potential code vulnerabilities, ensuring that the automation code meets quality standards.

Analyze Performance Impact: Data science is integral in analyzing the performance impact of the conveying system. Predictive analytics models can assess the system's efficiency under different conditions, enabling informed decision-making to optimize performance.

Conduct Operator Training: Machine learning algorithms can simulate various scenarios, providing a virtual training environment for operators. Data science contributes by analyzing operator performance data to tailor training programs, ensuring optimal skill development.

Test New System Concepts and Modification Requests: Data science supports testing new concepts and modifications by predicting the potential impact on the system. Analyzing historical data and performance metrics assists in making informed decisions regarding the adoption of new concepts or modifications.

In summary, the virtual commissioning function for material handling and warehousing systems relies on data science to perform crucial activities efficiently. The integration of data science not only enhances the virtual commissioning process but also contributes to achieving business agility goals such as improving behavioral and situational awareness, enabling inclusive and augmented decision-making, and creating dynamic processes and resources for fast execution (Jain et al., 2017; Lechler et al., 2019; Metzner et al., 2019; Qin & Dong, 2020; Sajid et al., 2021; Suss et al., 2015).

4.3.2.12 Virtual commissioning for production lines

The function responsible for "Virtual Commissioning for Production Lines" is a critical component of modern manufacturing, aimed at optimizing production processes through virtual simulations before physical implementation. This function encompasses activities as shown in *Figure 205,* such as defining mechatronic engineering models, preparing virtual commissioning environments, validating engineering models, executing simulations, conducting virtual commissioning tests, operator training, and testing new cell concepts and modification requests.

Define Mechatronic Engineering Model: This involves creating a comprehensive digital model that represents the mechanical, electrical, and software components of the production line. Data science can be applied to analyze historical data, simulate potential variations, and optimize the creation of an accurate mechatronic engineering model.

Prepare Virtual Commissioning Environment: Data science contributes to preparing the virtual commissioning environment by analyzing real-world data to simulate diverse operational scenarios. Machine learning algorithms can assist in optimizing the environment for various conditions, ensuring a robust simulation platform.

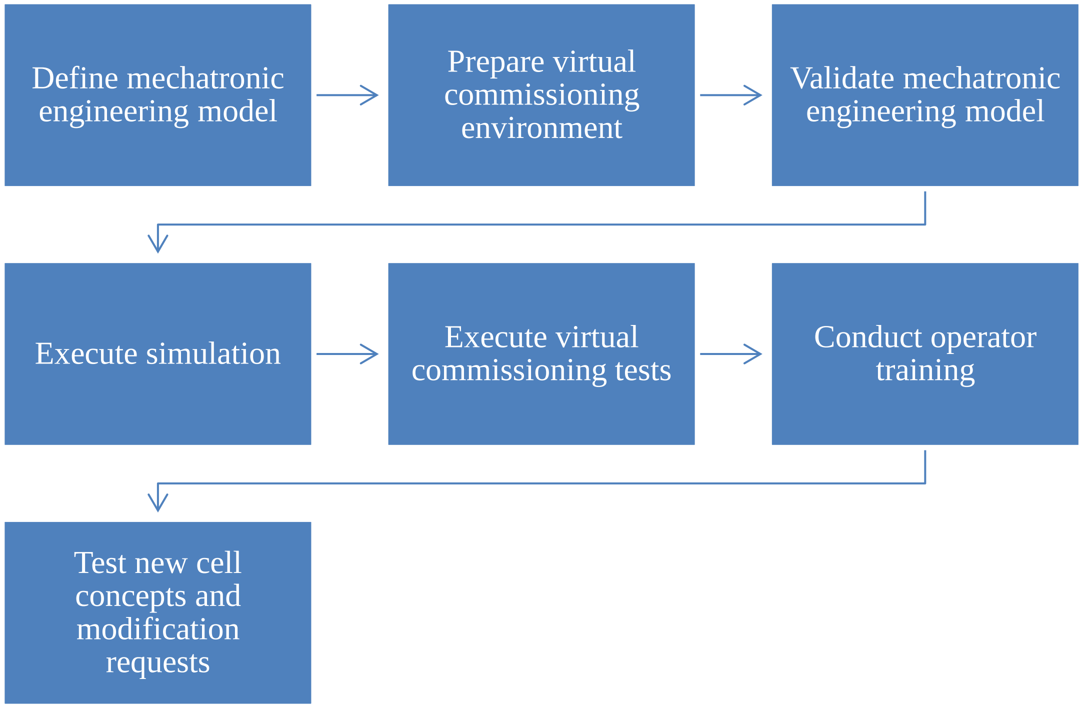

Figure 206 Typical Process of Virtual commissioning for production lines. Source: Author

Validate Mechatronic Engineering Model: Validation of the engineering model involves ensuring that it accurately represents the physical production line. Data science-driven analytics can compare the model against historical performance data, identifying discrepancies and refining the model for improved accuracy.

Execute Simulation: Executing simulations involves running virtual scenarios to assess the performance of the production line. Data science can optimize simulation parameters based on historical data, ensuring that the simulations provide realistic and insightful results.

Execute Virtual Commissioning Tests: Virtual commissioning tests simulate the actual commissioning process without physical implementation. Data science enhances this by analyzing simulated test results, identifying potential issues, and optimizing the commissioning process for efficiency.

Conduct Operator Training: Operator training involves using virtual environments to familiarize operators with the production line. Data science can personalize training modules based on individual learning patterns, ensuring more effective and customized operator training.

Test New Cell Concepts and Modification Requests: Testing new cell concepts and modification requests is virtually a proactive approach to assessing potential changes. Data science facilitates this by analyzing the impact of proposed modifications on the virtual production line, enabling informed decision-making before implementation.

In conclusion, the function of "Virtual Commissioning for Production Lines" integrates data science to enhance various activities, from model creation to virtual testing and operator training. The application of data science not only improves the accuracy and effectiveness of these activities but also significantly contributes to achieving business agility goals by fostering awareness, enabling inclusive decision-making, and enhancing dynamic processes and resource allocation for fast execution in virtual commissioning scenarios. This integrated approach aligns with the modern paradigm of smart and agile manufacturing practices (Dahl et al., 2016; Lechler et al., 2019; Mathias et al., 2014; Sub et al., 2016; Suss et al., 2015).

4.3.2.13 Virtual commissioning for production machines

The function responsible for "Virtual Commissioning for Production Machines" plays a crucial role in optimizing manufacturing processes by employing virtual simulations. This section explores the key activities within this function such as *Figure 207*, including defining simulation models, preparing virtual commissioning environments, performing virtual commissioning tests, conducting operator training, and testing new machine concepts and modification requests. Additionally, the discussion delves into how data science can be integrated into each activity to enhance efficiency and effectiveness.

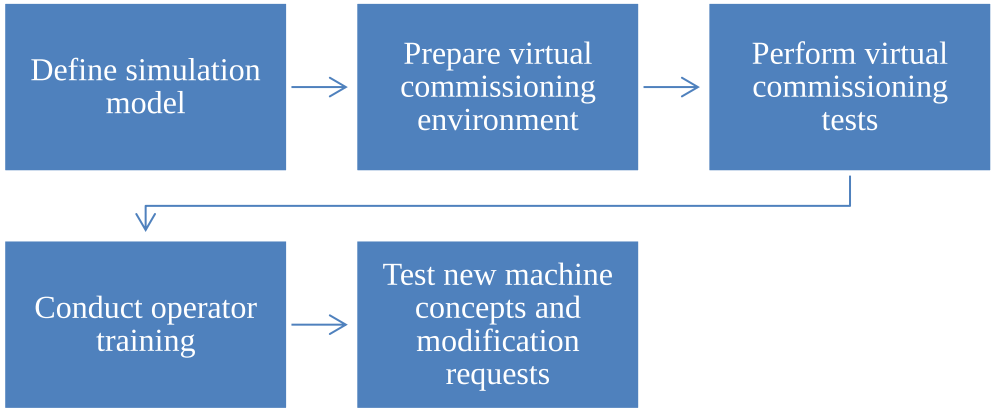

Figure 208 Typical Process of Virtual commissioning for production machines. Source: Author

Define Simulation Model: This activity involves creating a comprehensive simulation model that replicates the behavior and functionalities of production machines. Data science contributes by analyzing historical machine data to ensure accurate representation, utilizing machine learning algorithms to predict potential issues, and optimizing the simulation model for realistic testing scenarios.

Prepare Virtual Commissioning Environment: Data science aids in preparing the virtual commissioning environment by optimizing the simulation parameters based on historical and real-time data. Predictive analytics models can anticipate environmental conditions, ensuring that the virtual commissioning closely mirrors actual production environments, thus enhancing the reliability of the tests.

Perform Virtual Commissioning Tests: During virtual commissioning tests, data science is utilized for real-time analysis of simulated machine behavior. Machine learning algorithms can identify anomalies or deviations from expected outcomes, providing insights into potential issues before physical implementation. This proactive approach minimizes risks and accelerates the commissioning process.

Conduct Operator Training: Data science contributes to operator training by analyzing user interactions within the virtual commissioning environment. This enables the customization of training programs based on individual learning patterns, enhancing the effectiveness of operator training, and ensuring optimal performance during actual machine operation.

Test New Machine Concepts and Modification Requests: This activity involves testing novel machine concepts or modifications in the virtual environment before implementation. Data science facilitates this process by analyzing design data, predicting the impact of changes, and providing insights into potential performance improvements or challenges. This ensures informed decision-making before committing to physical changes.

In summary, the function of "Virtual Commissioning for Production Machines" is enhanced by integrating data science into key activities, from defining simulation models to conducting operator training. By achieving business agility goals through improved behavioral and situational awareness, inclusive and augmented decision-making, and the creation of dynamic processes and resources, data science contributes to a more efficient, responsive, and optimized virtual commissioning process within the broader scope of supply chain collaboration and material management (Dahl et al., 2016; Lechler et al., 2019; Sajid et al., 2021; Sub et al., 2016; Suss et al., 2015).

4.3.2.14 Virtual commissioning for machine tools

The Virtual Commissioning for Machine Tools function is a critical aspect of modern manufacturing processes, aiming to streamline and optimize machine commissioning through virtual simulations. This section delves into the activities encompassed within this function as shown in *Figure 209* and explores how data science can be employed to enhance efficiency and agility.

Define Functional Machine Behavior Model: This activity involves creating a virtual representation of the machine's behavior. Data science contributes by analyzing historical machine behavior data to refine and optimize the functional model, ensuring accuracy and reliability in the virtual environment.

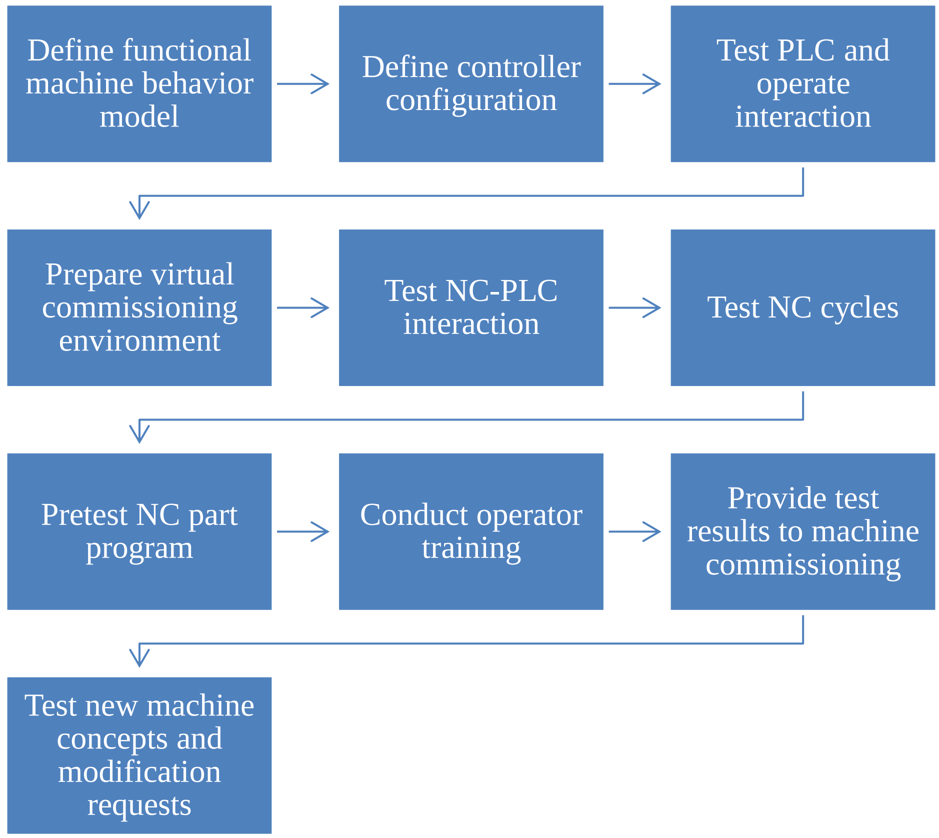

Figure 210 Typical Process of Virtual commissioning for machine tools. Source: Author

Define Controller Configuration: Data science aids in configuring the machine controller by utilizing algorithms to optimize controller settings based on historical performance data. This ensures that the virtual configuration aligns with real-world scenarios.

Test PLC and Operate Interaction: During the testing phase, data science can simulate PLC interactions and machine operations. Machine learning algorithms can predict potential issues in the interaction, allowing for proactive adjustments before the actual commissioning process.

Prepare Virtual Commissioning Environment: Data science supports the preparation of the virtual commissioning environment by automating the setup process based on historical data and predefined parameters. This ensures a consistent and reliable testing environment.

Test NC-PLC Interaction and NC Cycles: Data science is employed to analyze and optimize the interaction between numerical control (NC) systems and programmable logic controllers (PLC). Machine learning models can predict and prevent potential errors in NC cycles, enhancing the reliability of the virtual commissioning process.

Pretest NC Part Program: This activity involves pretesting the numerical control part program. Data science contributes by simulating various scenarios and predicting the program's performance, ensuring that it meets the desired specifications before actual implementation.

Conduct Operator Training: Data science supports operator training by creating simulated training scenarios and utilizing predictive analytics to identify areas for improvement. This ensures that operators are well-prepared for machine commissioning tasks.

Provide Test Results to Machine Commissioning: Data science generates comprehensive test results by analyzing virtual commissioning data. Machine learning algorithms can identify patterns, anomalies, and areas for improvement, providing valuable insights to enhance the machine commissioning process.

Test New Machine Concepts and Modification Requests: Data science assists in testing new machine concepts and modification requests by simulating their impact on machine behavior. Predictive modeling ensures that potential issues are identified and addressed in the virtual environment before implementation.

In summary, the integration of data science into Virtual Commissioning for Machine Tools not only enhances the efficiency of commissioning activities but also significantly improves business agility. By utilizing predictive analytics, machine learning, and AI-driven tools, this function can achieve a heightened level of awareness, facilitate inclusive and augmented decision-making, and create dynamic processes and resources for swift execution, thereby ensuring a more agile and adaptive manufacturing environment (Lechler et al., 2019; Luo et al., 2010; Mathias et al., 2014; Schamp et al., 2019; Suss et al., 2015; Xia et al., 2019).

4.3.2.15 Mitigation Strategies for Challenges in Adoption of Data Science

Table 32 outlines the Data Science use cases, challenges, risks, and mitigation strategies for each process in Automation Engineering and Commissioning:

Table 32 Data Science Use Cases for the various process in Automation Engineering and commissioning. Source: Author

Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
Automation Engineering	Predictive maintenance, Simulation-based validation	1. Lack of skilled workforce 2. Data quality and availability 3. Integration with existing systems	1. Equipment breakdowns and downtime 2. Inaccurate decision-making 3. System incompatibility	1. Invest in training programs 2. Implement data quality checks 3. Collaborate with IT for seamless integration
Automation Engineering Project Management	Predictive analytics for project timelines	1. Lack of skilled workforce 2. Integration with existing systems 3. Lack of standardization	1. Project delays and increased costs 2. Inefficient processes 3. System incompatibility	1. Invest in training programs 2. Collaborate with IT for seamless integration

Table 32 Data Science Use Cases for the various process in Automation Engineering and commissioning. Source: Author				
Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
				3. Establish standardized protocols
Storage and Material Transportation System Engineering	Predictive modeling for optimization	1. Data quality and availability 2. Lack of skilled workforce 3. Integration with existing systems	1. Inaccurate decision-making 2. Equipment breakdowns and downtime 3. System incompatibility	1. Implement data quality checks 2. Invest in training programs 3. Collaborate with IT for seamless integration
Industrial Communication	Anomaly detection, Predictive analytics	1. Integration with existing systems 2. Data quality and availability 3. Privacy and security concerns	1. Data breaches and leaks 2. Inefficient processes 3. System downtime	1. Implement robust data security measures 2. Invest in data quality checks 3. Collaborate with IT for seamless integration

Table 32 Data Science Use Cases for the various process in Automation Engineering and commissioning. Source: Author

Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
Industrial Recognition and Identification	Image recognition, Predictive modeling	1. Data quality and availability 2. Lack of standardization 3. Integration with existing systems	1. Inaccurate decision-making 2. Data breaches and leaks 3. System incompatibility	1. Implement data quality checks 2. Establish standardized protocols 3. Collaborate with IT for seamless integration
Machine Connectivity	Predictive maintenance, IoT integration	1. Lack of skilled workforce 2. Integration with existing systems 3. Data quality and availability	1. System downtime 2. Inefficient processes 3. Data breaches and leaks	1. Invest in training programs 2. Collaborate with IT for seamless integration 3. Implement data quality checks
Drive Train Engineering and Configuration	Predictive maintenance, Simulation-based validation	1. Data quality and availability 2. Integration with existing systems 3. Lack of standardization	1. Inefficient processes 2. Equipment breakdowns and downtime	1. Implement data quality checks 2. Invest in training programs

Table 32 Data Science Use Cases for the various process in Automation Engineering and commissioning. Source: Author				
Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
			3. System incompatibility	3. Establish standardized protocols
Industrial Network Security	Anomaly detection, Threat intelligence	1. Privacy and security concerns 2. Integration with existing systems 3. Lack of standardization	1. Data breaches and leaks 2. System downtime 3. Inefficient processes	1. Implement robust data security measures 2. Establish standardized protocols 3. Invest in threat intelligence
Industrial Network Security Monitoring	Anomaly detection, Threat intelligence	1. Privacy and security concerns 2. Integration with existing systems 3. Lack of standardization	1. Data breaches and leaks 2. System downtime 3. Inefficient processes	1. Implement robust data security measures 2. Establish standardized protocols 3. Invest in threat intelligence
Machine Safety	Predictive maintenance, Simulation-	1. Lack of skilled workforce	1. Equipment breakdowns and downtime	1. Invest in training programs

Table 32 Data Science Use Cases for the various process in Automation Engineering and commissioning. Source: Author

Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
	based validation	2. Data quality and availability 3. Integration with existing systems	2. Inaccurate decision-making 3. System incompatibility	2. Implement data quality checks 3. Collaborate with IT for seamless integration
Virtual Commissioning of Material Handling and Warehousing System	Simulation-based optimization, Predictive analytics	1. Lack of skilled workforce 2. Integration with existing systems 3. Data quality and availability	1. Inefficient processes 2. Equipment breakdowns and downtime 3. Inaccurate decision-making	1. Invest in training programs 2. Implement data quality checks 3. Collaborate with IT for seamless integration
Virtual Commissioning for Production Lines	Simulation-based optimization, Predictive analytics	1. Lack of skilled workforce 2. Integration with existing systems 3. Data quality and availability	1. Inefficient processes 2. Equipment breakdowns and downtime 3. Inaccurate decision-making	1. Invest in training programs 2. Implement data quality checks 3. Collaborate with IT for

Table 32 Data Science Use Cases for the various process in Automation Engineering and commissioning. Source: Author				
Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
				seamless integration
Virtual Commissioning for Production Machines	Simulation-based optimization, Predictive analytics	1. Lack of skilled workforce 2. Integration with existing systems 3. Data quality and availability	1. Inefficient processes 2. Equipment breakdowns and downtime 3. Inaccurate decision-making	1. Invest in training programs 2. Implement data quality checks 3. Collaborate with IT for seamless integration
Virtual Commissioning for Machine Tools	Simulation-based optimization, Predictive analytics	1. Lack of skilled workforce 2. Integration with existing systems 3. Data quality and availability	1. Inefficient processes 2. Equipment breakdowns and downtime 3. Inaccurate decision-making	1. Invest in training programs 2. Implement data quality checks 3. Collaborate with IT for seamless integration

Table 32 also illustrates how data science can be applied across various processes in Automation Engineering and Commissioning to achieve business goals. However, organizations may face challenges such as lack of skilled workforce, data quality issues, and integration complexities. Mitigation strategies include investing in training programs, implementing data quality checks, and collaborating with IT for seamless integration.

4.3.3 Mitigation Strategies for Challenges in Adoption of Data Science in Manufacturing building and asset management

In the realm of Manufacturing Engineering, the application of data science in Manufacturing Building and Asset Management is instrumental across various interconnected sub-functions. These processes collectively contribute to optimizing construction, planning, and maintenance within manufacturing facilities. The key sub-functions within this domain are shown in Figure 114.

Incorporating data science within these sub-functions enhances decision-making processes, reduces operational risks, and contributes to the overall agility and competitiveness of the manufacturing engineering function. The effective integration of data science methodologies empowers organizations to stay ahead in a rapidly evolving manufacturing landscape.

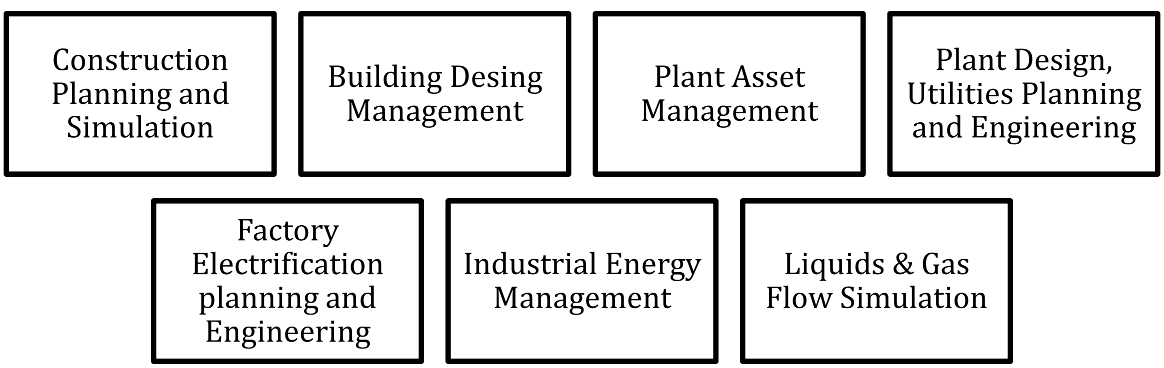

Figure 211 Typical Functions in Manufacturing building and asset management
Source: Author

The integration of data science into Manufacturing Building and Asset Management within the manufacturing engineering function is transformative. It not only optimizes existing processes but also opens avenues for innovation, resilience, and sustainable practices. This strategic adoption positions manufacturing organizations to thrive in an increasingly data-centric and competitive landscape (Gyulai et al., 2020; Sadati et al., 2018; Flath & Stein, 2018; Farghaly et al., 2017; Campos et al., 2017).

4.3.3.1 Construction planning and simulations.

The Construction Planning and Simulations function plays a pivotal role in orchestrating the planning and execution of construction projects. This section delves into the key activities performed within this function as shown in *Figure 212*, namely planning construction projects, executing 4D planning, performing load and thermal analysis, and conducting Green Building simulations. Additionally, the discussion explores how data science can be harnessed to improve business agility in this context.

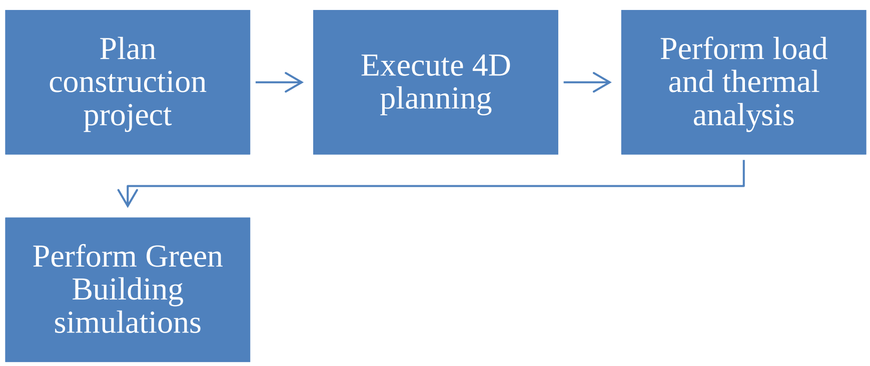

Figure 213 Typical processs in Construction planning and simulations. Source: Author

Plan Construction Project: Planning a construction project involves defining project goals, scope, timelines, and resource requirements. Data science contributes by analyzing historical project data to optimize resource allocation, predict potential risks, and enhance the accuracy of project timelines. Machine learning models can assist in forecasting resource demands and identifying optimal project strategies based on historical performance data.

Execute 4D Planning: 4D planning integrates the element of time into the 3D model of a construction project. Data science facilitates this process by employing algorithms that consider project schedules, resource availability, and potential conflicts. Machine learning algorithms can optimize the sequencing of construction activities, ensuring efficient execution and minimizing delays.

Perform Load and Thermal Analysis: Load and thermal analysis are critical for assessing the structural integrity and energy efficiency of construction projects. Data science tools, such as Finite Element Analysis (FEA) models, can simulate and analyze complex load scenarios, predicting how structures respond under different conditions. This enables engineers to optimize designs for safety and energy efficiency.

Perform Green Building Simulations: Green Building simulations evaluate the environmental impact and sustainability of construction projects. Data science aids in this activity by modeling and simulating factors such as energy consumption, carbon emissions, and resource usage. Predictive modeling can assist in identifying eco-friendly materials and design choices, contributing to the overall sustainability of the construction project.

In summary, the Construction Planning and Simulations function, supported by data science, encompasses activities ranging from traditional project planning to advanced simulations for sustainable construction. The integration of data science enhances business agility by improving behavioral and situational awareness, enabling inclusive and augmented decision-making, and creating dynamic processes and resource allocation for swift execution (Rogovenko & Zaitseva, 2017; Li et al., 2015; Akhavian, 2015; Akhavian & Behzadan, 2013).

4.3.3.2 Building design management

The function of Building Design Management encompasses a range of critical activities in overseeing the design and construction processes. This section explores the key responsibilities within this function as shown in *Figure 214*, including managing building designs, overseeing construction project deliverables, implementing workgroup change control, and integrating designs into the overall environment. Additionally, the discussion delves into how data science can be applied to optimize each activity and subsequently explores how data science can enhance business agility goals within this function.

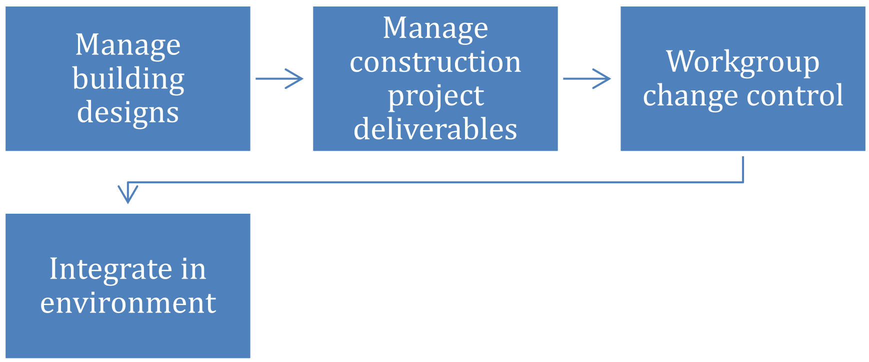

Figure 215 Typical Process in Building design management. Source: Author

Managing Building Designs: Managing building designs involves overseeing the architectural and engineering aspects of a construction project. Data science can contribute by utilizing Building Information Modeling (BIM) and analytics to enhance design efficiency, evaluate design options, and optimize resource utilization. Predictive modeling can also help anticipate potential design challenges, facilitating proactive decision-making.

Managing Construction Project Deliverables: Efficient management of construction project deliverables is crucial for ensuring project timelines and quality standards are met. Data science can be applied to automate document management, track project milestones, and predict potential delays. Machine learning algorithms can analyze historical project data to identify patterns, allowing for more accurate project planning and risk mitigation.

Workgroup Change Control: Implementing workgroup change control involves managing modifications to the original design or project plan. Data science contributes by developing change control algorithms that assess the impact of proposed changes, predict potential risks, and recommend optimal courses of action. This data-driven approach ensures that changes are implemented seamlessly without compromising project integrity.

Integrate in Environment: Integrating designs into the environment involves aligning building designs with the surrounding landscape and infrastructure. Data science can assist by analyzing geographic data, environmental factors, and infrastructure requirements to optimize design integration. Geographic Information System (GIS) and machine learning can enhance decision-making by considering diverse data sources.

In summary, Building Design Management involves overseeing crucial aspects of construction projects, and data science plays a pivotal role in optimizing activities such as design management, project deliverables, change control, and design integration. Furthermore, the integration of data science enhances business agility by improving behavioral and situational awareness, enabling inclusive and augmented decision-making, and creating dynamic processes and resources for fast execution within this function. This data-centric approach ensures a streamlined and agile Building Design Management process, contributing to the success of construction projects (Mandičák et al., 2021; Abdelrahman et al., 2021; Brown et al., 2020; Leiman & Leppänen, 2020; Loyola, 2018; Sulistyah & Hong, 2019).

4.3.3.3 Plant asset management

The function responsible for Plant Asset Management is integral to ensuring the efficient operation and maintenance of assets within a plant or industrial setting. This section explores the key activities performed by this function as shown in *Figure 216*, namely managing asset information, managing asset reliability and performance, and asset publishing and exchange. Additionally, it delves into how data science can be applied to enhance these activities. Subsequently, a separate section explores how data science contributes to achieving various business agility goals within this function.

Figure 217 Typical Process in Plant asset management. Source: Author

Manage Asset Information: This activity involves the organized storage, retrieval, and maintenance of comprehensive asset information. Data science can contribute by implementing systems that utilize machine learning algorithms to automatically categorize, tag, and update asset information. Predictive analytics models can forecast potential maintenance needs based on historical data, ensuring accurate and timely asset information management.

Manage Asset Reliability and Performance: Ensuring the reliability and optimal performance of plant assets is crucial for operational efficiency. Data science can be applied to predict asset failures through the analysis of real-time sensor data, historical performance metrics, and external factors. Predictive maintenance models can recommend proactive measures, minimizing downtime and maximizing asset reliability.

Asset Publishing and Exchange: This activity involves sharing asset-related information with relevant stakeholders and exchanging data with external systems. Data science contributes by implementing secure and efficient data exchange protocols. Natural Language Processing (NLP) algorithms can facilitate seamless communication by extracting and translating key information from diverse data sources, promoting effective asset publishing and exchange.

In summary, the Plant Asset Management function encompasses activities such as managing asset information, ensuring reliability and performance, and facilitating asset publishing and exchange. Data science plays a pivotal role in enhancing these activities through predictive analytics, machine learning, and AI-driven insights. Moreover, data science contributes significantly to achieving business agility goals within this function, fostering behavioral awareness, situational awareness, inclusive decision-making, augmented decision-making, and creating dynamic processes and resources for fast execution. This integration of data science supports the overall efficiency, adaptability, and agility of the Plant Asset Management function in complex industrial settings (Ahonen et al., 2019; Athoillah & Pratiwi, 2018; Campos et al., 2017; Cesa & Press, 2020; Kortelainen et al., 2015; Teoh et al., 2023; Utz & Falcioni, 2018).

4.3.3.4 Plant design, utilities planning and engineering.

The function responsible for "Plant Design, Utilities Planning, and Engineering" plays a pivotal role in shaping the physical and operational aspects of manufacturing facilities. This section explores the various activities within this function as shown in *Figure 218*, delving into how data science can enhance each process. Additionally, it discusses how leveraging data science contributes to achieving specific business agility goals.

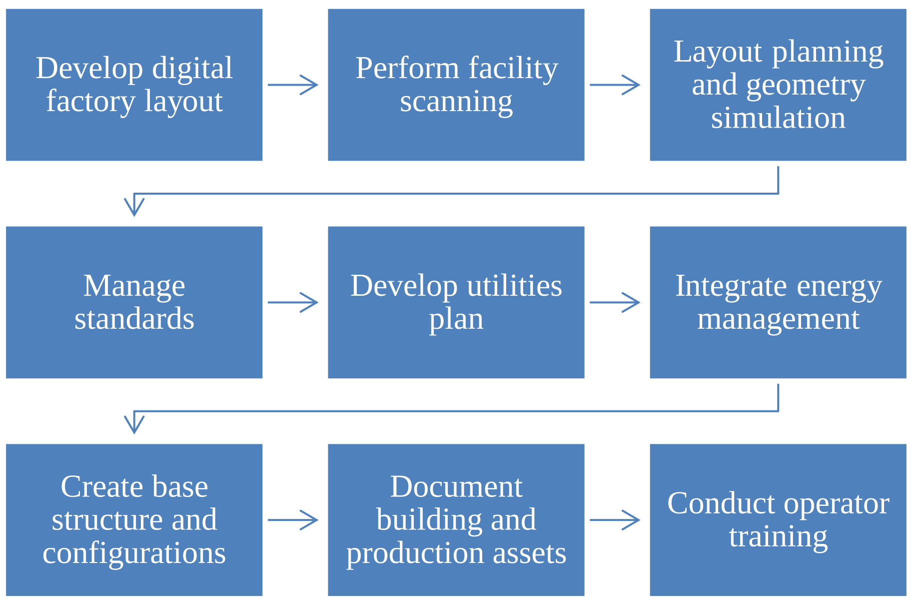

Figure 219 Typical Process in Plant design, utilities planning and engineering. Source: Author

Develop Digital Factory Layout: This activity involves creating a digital representation of the factory layout, considering space optimization and workflow efficiency. Data science supports this process by utilizing simulation models and optimization algorithms to iteratively design layouts that enhance productivity and minimize bottlenecks.

Perform Facility Scanning: Facility scanning employs technologies like LiDAR or 3D scanning to capture the existing physical structure of the facility. Data science aids in processing and interpreting scanned data, providing accurate representations for further design and planning activities.

Layout Planning and Geometry Simulation: Data science enables advanced geometry simulations to assess the impact of different layouts on operational efficiency. Simulation models can predict workflow dynamics, allowing for informed decisions on layout planning to enhance overall productivity.

Manage Standards: Data science contributes to standard management by analyzing historical data to identify best practices and compliance standards. This ensures that the facility design aligns with industry regulations and optimized operational benchmarks.

Develop Utilities Plan: This activity involves planning for essential utilities such as water, electricity, and HVAC systems. Data science aids in optimizing utility plans by analyzing usage patterns, predicting demand, and recommending efficient configurations for utility systems.

Integrate Energy Management: Leveraging data science, energy management is optimized through predictive analytics models that analyze energy consumption patterns, identify inefficiencies, and recommend strategies for energy conservation, aligning with sustainability goals.

Create Base Structure and Configurations: Data science supports the creation of base structures and configurations by utilizing parametric modeling and generative design algorithms. This ensures that the physical structure is designed for maximum efficiency and adaptability.

Document Building and Production Assets: Data science aids in asset documentation by implementing digital twin technologies. This involves creating virtual replicas of physical assets, allowing for real-time monitoring, predictive maintenance, and efficient documentation.

Conduct Operator Training: Operator training benefits from data-driven simulations and virtual reality applications. Data science supports the creation of realistic training scenarios, enabling operators to familiarize themselves with the facility layout and operations in a risk-free environment.

In summary, the integration of data science into the "Plant Design, Utilities Planning, and Engineering" function enhances various activities involved in facility design and planning. From creating digital layouts to optimizing energy management and improving operator training, data science contributes to operational efficiency. Moreover, by achieving specific business agility goals, such as improving behavioral and situational awareness, enabling inclusive and augmented decision-making, and creating dynamic processes and resources, data science becomes a catalyst for enhancing overall agility within this crucial function (Daniel & Kapoor, 2023; Davé & Ball, 2013; Flath & Stein, 2018; Hovanec et al., 2015; Konstantin et al., 2016; Yuri et al., 2019; Zadeh & Shahbazy, 2020; Zarte et al., 2017).

4.3.3.5 Factory electrification planning and engineering

The function responsible for "Factory Electrification Planning and Engineering" encompasses a series of critical activities to ensure the efficient and optimized electrification of factory systems. This section explores the key activities performed within this function as shown in *Figure 220*, delving into the configuration of cabinets and motor control centers (MCC), definition of low voltage (LV) component standards, development of LV component architecture, engineering integration for electrification and automation, and the integration of LV components into the overall automation concept.

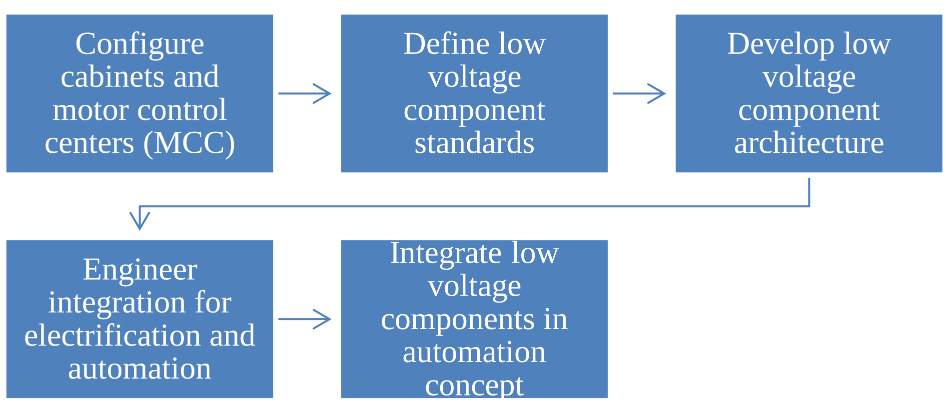

Figure 221 Typical Process in Factory electrification planning and engineering. Source: Author

Configure Cabinets and Motor Control Centers (MCC): This involves the configuration of cabinets and motor control centers, ensuring they are designed to accommodate low voltage components effectively. Data science can optimize the configuration process by analyzing historical data on equipment performance and energy consumption. Predictive modeling can guide the selection and layout of components to enhance efficiency and reduce energy consumption.

Define Low Voltage Component Standards: Defining standards for low voltage components establishes a framework for consistency and interoperability. Data science can analyze performance data of different components to establish standards that optimize performance, reliability, and energy efficiency. Machine learning algorithms can predict the impact of component variations on overall system performance.

Develop Low Voltage Component Architecture: Developing the architecture involves designing the arrangement and interaction of low voltage components within the electrification system. Data science contributes by analyzing historical architectures, evaluating performance metrics, and suggesting optimal configurations based on desired outcomes and efficiency goals.

Engineer Integration for Electrification and Automation: Engineering integration involves ensuring seamless coordination between electrification and automation systems. Data science can optimize the engineering process by analyzing data on system interactions, identifying potential bottlenecks, and suggesting improvements to enhance overall integration efficiency.

Integrate Low Voltage Components in Automation Concept: Integrating low voltage components into the broader automation concept ensures a cohesive and synchronized operational framework. Data science can aid in integration by analyzing real-time data from low voltage components and automating decision-making processes based on dynamic conditions, enhancing overall system responsiveness.

In summary, the Factory Electrification Planning and Engineering function involves critical activities for optimizing electrification systems. The integration of data science enhances these activities by optimizing configuration processes, establishing efficient standards and architectures, ensuring seamless integration, and improving overall system responsiveness. Furthermore, data science contributes significantly to achieving business agility goals by improving behavioral and situational awareness, enabling inclusive and augmented decision-making, and creating dynamic processes and resources for fast execution. This integration of data science not only improves operational efficiency but also positions the function for agile responses to dynamic industrial landscapes (Davé et al., 2015; Junaidi & Shaaban, 2018; Kumar et al., 2021; Martinez-Ceseña et al., 2015; Mulrennan et al., 2018; Ning et al., 2021).

4.3.3.6 Industrial energy management

The function of Industrial Energy Management encompasses a range of activities aimed at optimizing energy consumption within industrial settings. This section explores the key activities involved in this function as shown in *Figure 222*, highlighting how data science can enhance each stage of the process. Additionally, it delves into how utilizing data science can improve business agility in Industrial Energy Management, addressing specific business agility goals.

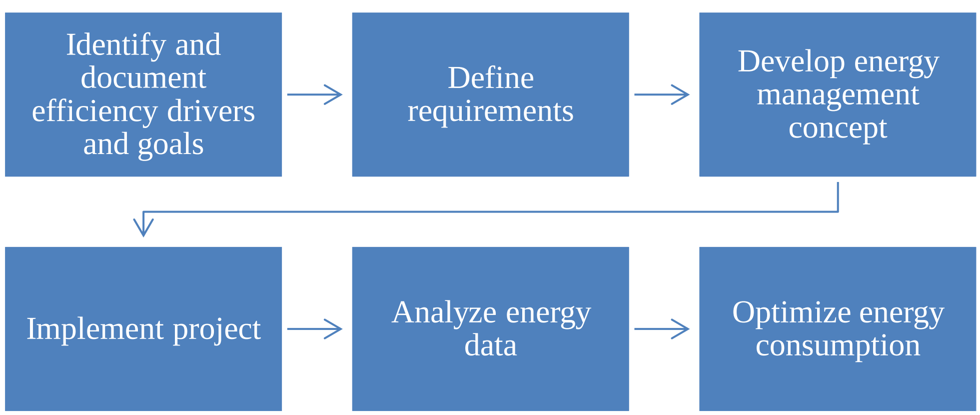

Figure 223 Typical Process in Industrial energy management. Source: Author

Identify and Document Efficiency Drivers and Goals: This initial activity involves identifying and documenting the key drivers influencing energy efficiency and establishing specific goals. Data science contributes by analyzing historical energy consumption patterns, identifying inefficiencies, and providing insights into potential efficiency drivers. Machine learning models can forecast future energy needs, assisting in setting realistic efficiency goals.

Define Requirements: Defining the requirements for energy management involves specifying the criteria and parameters that will guide the optimization process. Data science plays a role in this stage by analyzing contextual data, operational conditions, and regulatory requirements. This ensures that the defined requirements align with the specific needs of the industrial facility.

Develop Energy Management Concept: Data science contributes to the development of an energy management concept by simulating different scenarios and predicting outcomes. Through modeling and simulation, machine learning algorithms can assess the impact of various strategies on energy consumption, facilitating the creation of an effective energy management concept.

Implement Project: During project implementation, data science supports the integration of smart technologies for real-time monitoring and control. IoT devices and sensors generate vast amounts of data, and data science algorithms can analyze this data to identify deviations from energy efficiency targets and initiate corrective actions.

Analyze Energy Data: Data science is fundamental in the ongoing analysis of energy data. Advanced analytics, including anomaly detection and pattern recognition, enable the identification of trends, energy consumption peaks, and potential areas for improvement. This continuous analysis ensures that the energy management strategy remains aligned with efficiency goals.

Optimize Energy Consumption: The optimization of energy consumption involves refining strategies based on ongoing analysis and feedback. Data science utilizes predictive modeling to anticipate future energy demands, enabling proactive adjustments to optimize consumption. Machine learning algorithms can adapt to changing operational conditions, ensuring a responsive and adaptive approach to energy optimization.

In summary, Industrial Energy Management activities, from identifying efficiency drivers to optimizing energy consumption, benefit significantly from the integration of data science. The application of data science enhances efficiency, supports informed decision-making, and contributes to the achievement of energy management goals. Furthermore, the incorporation of data science addresses specific business agility goals, fostering behavioral awareness, situational awareness, inclusive decision-making, augmented decision-making, and the creation of dynamic processes and resources for fast execution. This integration ensures a more responsive, adaptive, and agile Industrial Energy Management system (Colmenares-Quintero et al., 2021; Herman et al., 2018; Molina-Solana et al., 2017; Sievers & Blank, 2023; Song et al., 2014).

4.3.3.7 Liquids and gas flow simulation

The function responsible for "Liquids and Gas Flow Simulation" plays a critical role in optimizing production processes and ensuring the efficient flow of liquids and gases within industrial systems. This section provides an overview of the activities performed by this function as shown in *Figure 224* and explores how data science can enhance each activity.

Define Piping and Environment Parameters: Involves specifying the characteristics of piping systems and the surrounding environment. Data science can contribute by analyzing historical data to determine optimal parameter values, ensuring accuracy and efficiency in simulations.

Validate Installed Base: Requires validating the existing infrastructure to ensure it aligns with simulation requirements. Data science techniques, such as anomaly detection algorithms, can assess the installed base, identify discrepancies, and recommend corrective actions.

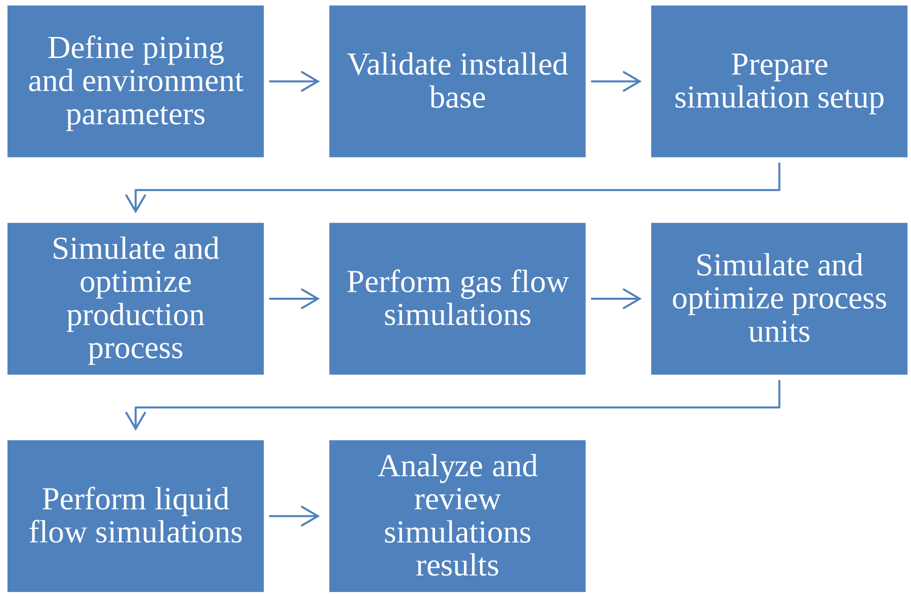

Figure 225 Typical Process Flow Liquids and gas flow simulation. Source: Author

Prepare Simulation Setup: Involves configuring the simulation environment, considering factors like fluid properties and system geometry. Data science can automate setup processes by analyzing past simulation configurations, streamlining the preparation phase.

Simulate and Optimize Production Process: Encompasses the actual simulation of the production process and optimizing it for efficiency. Data science, including machine learning, can analyze simulation results, identify bottlenecks, and suggest optimizations for enhanced production.

Perform Gas Flow Simulations: Focuses on simulating the flow of gases within the system. Data science applications, such as Computational Fluid Dynamics (CFD) models, can accurately model and analyze gas flow patterns for improved system understanding.

Simulate and Optimize Process Units: Involves simulating individual process units and optimizing their performance. Data science can leverage optimization algorithms to identify the most efficient configurations for each process unit.

Perform Liquid Flow Simulations: Like gas flow simulations, this activity centers on simulating liquid flow within the system. Data science can model complex liquid dynamics and provide insights into optimizing liquid flow processes.

Analyze and Review Simulation Results: Requires a comprehensive analysis of simulation outcomes to make informed decisions. Data science tools can automate result analysis, identify key performance indicators, and provide actionable insights for decision-makers.

In summary, the Liquids and Gas Flow Simulation function is crucial for optimizing industrial processes, and data science plays a pivotal role in enhancing each activity within this function. Furthermore, leveraging data science contributes to achieving various business agility goals, fostering a more adaptable and efficient simulation environment within the broader context of plant asset Management (Andric et al., 2019; Chen et al., 2021; Choi et al., 2013; Sun & Sakai, 2015).

4.3.3.8 Mitigation Strategies for Challenges in Adoption of Data Science

Below Table 33 outlines various data science use cases within the realm of manufacturing, focusing on processes related to building and asset management. In today's highly competitive manufacturing landscape, leveraging data science techniques is becoming increasingly essential for optimizing efficiency, reducing costs, and enhancing decision-making. However, alongside the potential benefits come several challenges and associated risks that need to be carefully addressed.

Table 33 categorizes different manufacturing processes, such as construction planning, building design management, plant asset management, and more, each accompanied by specific data science use cases. These use cases range from predictive modeling for project timelines to image recognition for design verification and predictive maintenance for asset reliability. While these applications hold promise for revolutionizing manufacturing operations, they also face common challenges such as the lack of skilled workforce, issues related to data quality and availability, and integration complexities with existing systems.

Moreover, failing to mitigate these challenges adequately poses risks such as project delays, increased costs, inaccurate decision-making, system incompatibility, data breaches, and equipment breakdowns. To counter these risks, organizations are advised to implement various mitigation strategies such as investing in training programs to develop a skilled workforce, implementing data quality checks, establishing standardized protocols, and collaborating closely with IT departments for seamless integration with existing systems.

Table 33 Data Science Use Cases for the various process in Manufacturing building and asset management. Source: Author

Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
Construction Planning and Simulations	Predictive modeling for project timelines	1. Lack of skilled workforce 2. Data quality and availability 3. Integration with existing systems	1. Project delays and increased costs 2. Inaccurate decision-making 3. System incompatibility	1. Invest in training programs 2. Implement data quality checks 3. Collaborate with IT for seamless integration
Building Design Management	Image recognition for design verification	1. Data quality and availability 2. Lack of standardization 3. Integration with existing systems	1. Inaccurate decision-making 2. Data breaches and leaks 3. System incompatibility	1. Implement data quality checks 2. Establish standardized protocols 3. Collaborate

Table 33 Data Science Use Cases for the various process in Manufacturing building and asset management. Source: Author				
Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
				with IT for seamless integration
Plant Asset Management	Predictive maintenance for asset reliability	1. Lack of skilled workforce 2. Data quality and availability 3. Integration with existing systems	1. Equipment breakdowns and downtime 2. Inaccurate decision-making 3. System incompatibility	1. Invest in training programs 2. Implement data quality checks 3. Collaborate with IT for seamless integration
Plant Design, Utilities Planning and Engineering	Simulation-based layout optimization	1. Data quality and availability 2. Integration with existing systems 3. Lack of standardization	1. Inefficient processes 2. Equipment breakdowns and downtime 3. Inaccurate decision-making	1. Implement data quality checks 2. Invest in training programs 3. Collaborate with IT for seamless integration

Table 33 Data Science Use Cases for the various process in Manufacturing building and asset management. Source: Author

Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
Factory Electrification Planning and Engineering	Predictive maintenance for electrical systems	1. Lack of skilled workforce 2. Data quality and availability 3. Integration with existing systems	1. Equipment breakdowns and downtime 2. Inaccurate decision-making 3. System incompatibility	1. Invest in training programs 2. Implement data quality checks 3. Collaborate with IT for seamless integration
Industrial Energy Management	Predictive analytics for energy optimization	1. Data quality and availability 2. Integration with existing systems 3. Lack of standardization	1. Inefficient processes 2. Equipment breakdowns and downtime 3. Inaccurate decision-making	1. Implement data quality checks 2. Invest in training programs 3. Collaborate with IT for seamless integration
Liquids and Gas Flow Simulation	Computational fluid dynamics for process optimization	1. Data quality and availability 2. Integration with existing systems	1. Inaccurate decision-making 2. System incompatibility	1. Implement data quality checks

Table 33 Data Science Use Cases for the various process in Manufacturing building and asset management. Source: Author				
Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
		3. Lack of skilled workforce	3. Equipment breakdowns and downtime	2. Invest in training programs 3. Collaborate with IT for seamless integration

This table demonstrates how data science can enhance various processes within Manufacturing Building and Asset Management to achieve business agility goals. However, organizations may face challenges such as lack of skilled workforce, data quality issues, and integration complexities. Mitigation strategies include investing in training programs, implementing data quality checks, and collaborating with IT for seamless integration. In summary, the table underscores the importance of data science in modern manufacturing processes while emphasizing the critical need for addressing associated challenges and risks through proactive mitigation strategies. By doing so, manufacturers can unlock the full potential of data-driven insights to drive operational excellence and competitive advantage in an ever-evolving industry landscape.

4.4 Mitigation Strategies for Challenges in Adoption of Data Science in Manufacturing Execution

In the realm of manufacturing, the effective application of data science in Manufacturing Execution plays a pivotal role in enhancing overall operational efficiency. This encompasses several key business processes listed below within a typical manufacturing setup.

- Manufacturing Execution Management and Control
- Shop Floor Logistics
- Production Monitoring and Analytics
- Cross Domain Integrations
- Quality Assurance and Defect Prevention
- Workforce Optimization
- Energy Management and Sustainability
- Continuous Improvement and Adaptive Strategies
- Supply Chain Optimization
- Real-time Decision Support
- Regulatory Compliance and Reporting
- Predictive Maintenance for Equipment
- Dynamic Resource Allocation

The pervasive influence of data science across Manufacturing Execution functions reshapes the traditional manufacturing landscape. From supply chain optimization to real-time decision support, regulatory compliance, and predictive maintenance, the integration of data science fosters a data-centric environment that drives efficiency, innovation, and adaptability in the manufacturing sector (Jain et al., 2017; Perzyk et al., 2011; Potekhin et al., 2020; Urbina Coronado et al., 2018).

4.4.1 Mitigation Strategies for Challenges in Adoption of Data Science in Manufacturing Execution Management and Control

In the realm of Manufacturing Execution Management and Control, the integration of data science methodologies can revolutionize several key business processes as shown in Figure 122. This section summarizes the different data science use cases in this domain, associated challenges and risk along with the proposed mitigation strategies that can be taken by organizations.

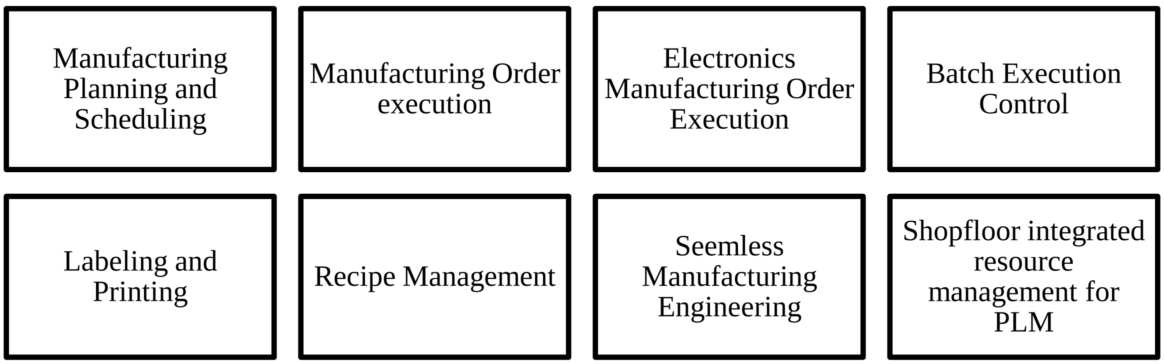

Figure 226 Typical Functions in Manufacturing Execution Management and Control. Source: Author

The integration of data science in Manufacturing Execution Management and Control represents a paradigm shift towards intelligent and data-driven manufacturing. The seamless integration of these technologies into traditional manufacturing processes paves the way for enhanced competitiveness, improved product quality, and greater agility in responding to the dynamic demands of the modern industrial landscape. As industries continue to embrace digital transformation, the role of data science in Manufacturing Execution Management and Control will undoubtedly be central to achieving and sustaining operational excellence (Kozjek et al., 2018; Krumeich et al., 2014; Potekhin et al., 2020; Qin & Dong, 2020; Sadati et al., 2018; Vazan et al., 2017).

4.4.1.1 Manufacturing Planning and Scheduling

The Manufacturing Planning and Scheduling function is pivotal in orchestrating the production processes efficiently. This multifaceted function encompasses activities as shown in *Figure 227* such as long-term planning, production capacity planning, pre-production checks and simulation, master production schedule management, production order scheduling, schedule optimization and updates, as well as what-if analysis and simulation, culminating in schedule reporting.

Performing Long Term Planning: Long-term planning involves setting the strategic direction for manufacturing operations over an extended horizon. Data science contributes by analyzing historical data, market trends, and business objectives. Predictive modeling aids in forecasting demand, optimizing resource utilization, and aligning production plans with organizational goals.

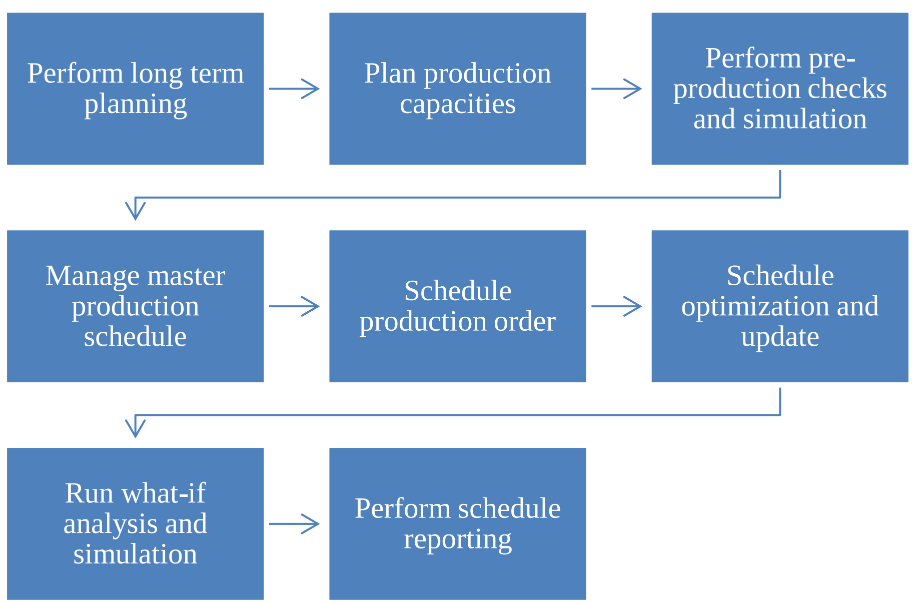

Figure 228 Typical Process Flow Manufacturing Planning and Scheduling. Source: Author

Planning Production Capacities: Data science optimizes production capacity planning by analyzing historical performance data, equipment utilization, and production constraints.

Machine learning algorithms can predict capacity bottlenecks, enabling proactive adjustments to ensure optimal utilization and avoid disruptions.

Performing Pre-Production Checks and Simulation: Data science facilitates pre-production checks and simulation by leveraging digital twins and simulation models. This allows for virtual testing of production scenarios, identifying potential issues, and optimizing processes before actual implementation. Machine learning enhances simulation accuracy by incorporating real-time data.

Managing Master Production Schedule: The master production schedule serves as the blueprint for manufacturing operations. Data science supports this activity by analyzing demand fluctuations, production constraints, and resource availability. Predictive analytics aids in creating a robust and adaptive master schedule that aligns with dynamic business needs.

Scheduling Production Order: Data science automates and optimizes the scheduling of production orders. By analyzing real-time data on order priorities, resource availability, and production constraints, machine learning algorithms can generate schedules that minimize lead times, enhance resource utilization, and meet customer demands efficiently.

Schedule Optimization and Update: Continuous schedule optimization is achieved through data-driven insights. Machine learning models analyze real-time data, identify bottlenecks, and dynamically adjust schedules for optimal efficiency. This ensures that production schedules remain responsive to changing conditions.

Running What-If Analysis and Simulation: What-if analysis and simulation involve exploring various scenarios to assess their impact on production outcomes. Data science facilitates this by creating predictive models that simulate different scenarios based on historical data, enabling informed decision-making and risk mitigation.

Performing Schedule Reporting: Schedule reporting involves providing stakeholders with insights into production schedules and performance. Data science enhances reporting by creating automated dashboards and analytics tools. This ensures that decision-makers have real-time visibility, enabling proactive responses to deviations from the plan.

In summary, the Manufacturing Planning and Scheduling function, enhanced by data science, encompasses a spectrum of activities crucial for effective production management. Leveraging AI for behavioral awareness, situational awareness, inclusive decision-making, augmented decision-making, dynamic processes, and dynamic resource allocation propels manufacturing towards heightened business agility, responsiveness, and efficiency within the broader framework of Supply Chain Collaboration and Material Management (De Modesti et al., 2020; Krenczyk et al., 2017; Li et al., 2015; Rossit et al., 2019; Zhu et al., 2017).

4.4.1.2 Manufacturing Order execution

The Manufacturing Order Execution function plays a pivotal role in the operational efficiency of manufacturing processes. This section explores the diverse activities encompassed by this function as shown in *Figure 229* and delves into how data science can optimize each activity. Additionally, a separate section addresses how data science can enhance business agility within this function by achieving specific goals.

Authoring and Defining Production Work Orders: Data science can streamline the authoring process by analyzing historical production data, predicting optimal order parameters, and automating the generation of work orders. This ensures accuracy and efficiency in initiating manufacturing processes.

Authorize and Certify Operation: Data science contributes to authorization and certification by implementing decision support systems. Machine learning models can assess compliance, evaluate operational risks, and provide recommendations, enhancing the accuracy and speed of authorization processes.

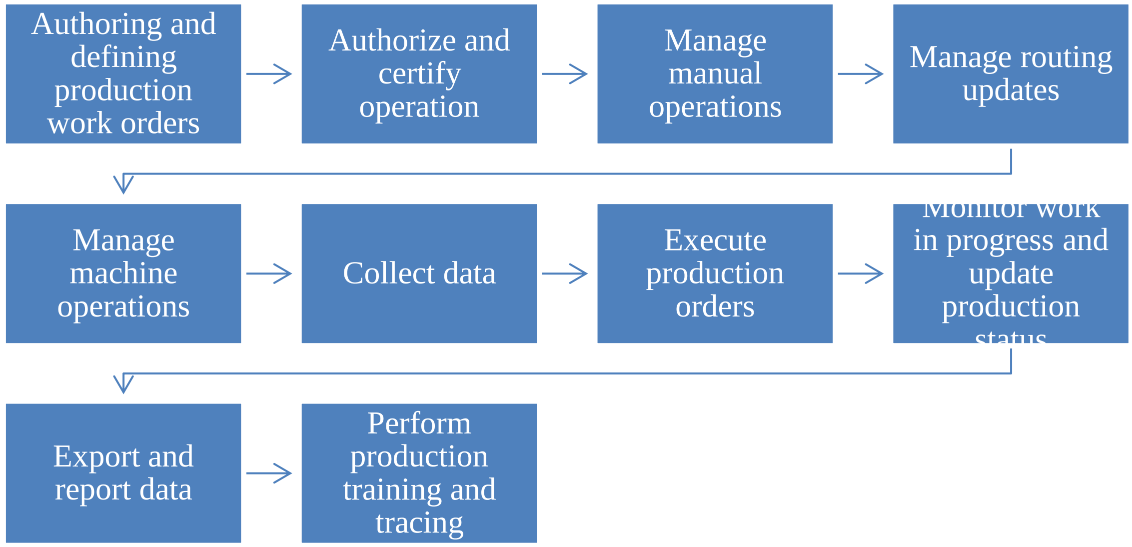

Figure 230 Typical Process in Manufacturing Order execution. Source: Author

Manage Manual Operations: Automated monitoring systems driven by data science can oversee manual operations. This involves real-time data analysis to ensure adherence to protocols, identify deviations, and facilitate timely interventions for manual processes.

Manage Routing Updates: Data science aids in managing routing updates by analyzing production data, identifying bottlenecks, and recommending route optimizations. This ensures that manufacturing processes are continually refined for maximum efficiency.

Manage Machine Operations: Machine learning algorithms can optimize machine operations by analyzing performance data, predicting equipment maintenance needs, and recommending adjustments. This proactive approach minimizes downtime and ensures the reliability of machine operations.

Collect Data: Data science is inherent in the collection of manufacturing data. Automated data collection systems, utilizing IoT devices and sensors, can capture real-time data, providing a comprehensive and accurate dataset for analysis.

Execute Production Orders: Automated execution of production orders is facilitated by data science-driven systems. Machine learning models can optimize production schedules, adapt to changing conditions, and ensure the timely execution of orders.

Monitor Work in Progress and Update Production Status: Data science enhances real-time monitoring by analyzing production data and updating statuses dynamically. This enables quick response to deviations, ensuring that work progresses smoothly and aligns with production goals.

Export and Report Data: Data science contributes to exporting and reporting by automating data analysis and report generation. Machine learning algorithms can identify key performance indicators, trends, and insights, streamlining the reporting process.

Perform Production Training and Tracing: Data science can improve training programs by analyzing performance data to identify skill gaps and tailor training content. Additionally, tracing manufacturing processes is enhanced through predictive analytics, ensuring accurate tracking of production steps.

In conclusion, the Manufacturing Order Execution function, with its diverse activities, benefits significantly from the integration of data science. From optimizing manual and machine operations to enhancing decision-making and business agility, data science plays a crucial role in ensuring efficiency, accuracy, and adaptability in manufacturing processes (Blum & Schuh, 2017; Groggert et al., 2018; Kozjek et al., 2018; Munro & Madan, 2016; Schuh et al., 2020; Schuh & Blum, 2016).

4.4.1.3 Electronics Manufacturing Order Execution

The Electronics Manufacturing Order Execution function is a pivotal aspect of the manufacturing process, responsible for the seamless execution of various activities involved in electronics manufacturing. This section delves into the intricacies of this function, encompassing tasks as shown in *Figure 231* from material identification to assembly testing and exploring how data science can enhance each step. Additionally, a separate section discusses how data science contributes to achieving key business agility goals within this function.

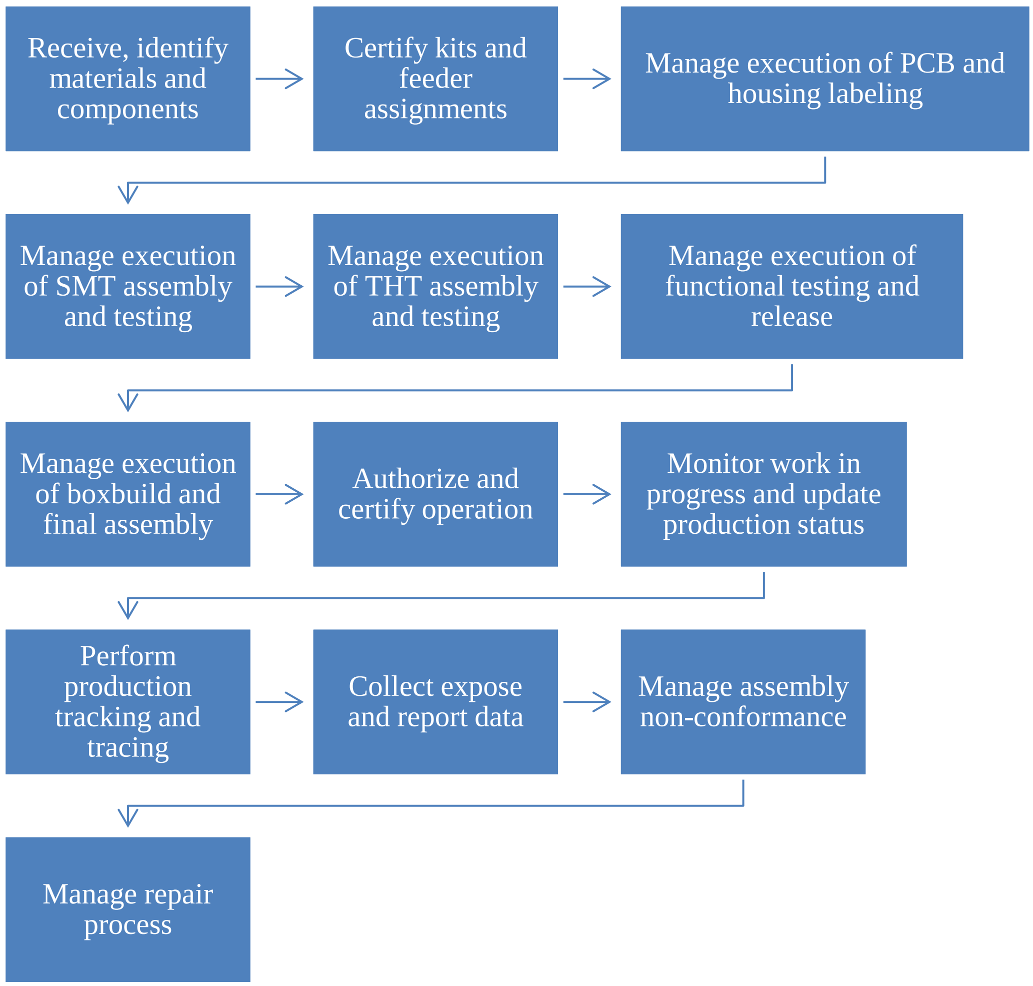

Figure 232 Typical Process in Electronics Manufacturing Order Execution. Source: Author

Receive, Identify Materials, and Components: Predictive analytics models can analyze historical data to forecast material arrival times, ensuring timely preparation and reducing bottlenecks in the production process.

Certify Kits and Feeder Assignments: Automated systems utilizing machine learning can assess kit certifications and feeder assignments, ensuring accuracy and compliance with production requirements.

Manage Execution of PCB and Housing Labeling: Computer vision algorithms can automate the labeling process by identifying PCBs and housing components, minimizing manual efforts, and improving efficiency.

Manage Execution of SMT Assembly and Testing: Predictive maintenance models can anticipate equipment failures during SMT assembly, reducing downtime and optimizing production schedules.

Manage Execution of THT Assembly and Testing: Quality analytics can analyze testing data to identify trends and potential defects during Through-Hole Technology (THT) assembly, facilitating proactive quality control measures.

Manage Execution of Functional Testing and Release: Automated testing frameworks utilizing machine learning can enhance the efficiency and accuracy of functional testing, ensuring the release of high-quality products.

Manage Execution of Box build and Final Assembly: Resource optimization algorithms can streamline the box build and final assembly process, ensuring optimal utilization of available resources and reducing production costs.

Authorize and Certify Operation: Blockchain technology can be integrated to create a secure and transparent authorization and certification process, ensuring the integrity of operational approvals.

Monitor Work in Progress and Update Production Status: Real-time monitoring systems using IoT sensors can provide continuous updates on work in progress, allowing for agile decision-making based on current production statuses.

Perform Production Tracking and Tracing: Blockchain-based traceability systems can enhance production tracking by providing an immutable and transparent record of the entire manufacturing process.

Collect, Expose, and Report Data: Automated reporting tools using natural language processing (NLP) can generate insightful reports from collected data, facilitating informed decision-making.

Manage Assembly Non-Conformance: Anomaly detection algorithms can identify non-conformance issues during assembly processes, enabling rapid response and corrective actions.

Manage Repair Process: Predictive maintenance models can assess the need for repairs based on historical data, minimizing unplanned downtimes, and optimizing repair processes.

In summary, the Electronics Manufacturing Order Execution function plays a pivotal role in the electronics manufacturing process. Leveraging data science across activities from material identification to assembly testing enhances efficiency, accuracy, and overall operational excellence. Additionally, the integration of data science contributes to achieving key business agility goals, fostering adaptability, inclusivity, and informed decision-making within the manufacturing order execution context (Blum & Schuh, 2017; Groggert et al., 2018; Herrera et al., 2019; Schuh & Blum, 2016).

4.4.1.4 Batch Execution Control

The function responsible for "Batch Execution Control" encompasses a series of activities that govern the planning, execution, monitoring, and analysis of batch production processes. These activities as shown in *Figure 233* are crucial for ensuring the efficient and quality-driven execution of production batches. In this section, I will delve into each activity and explore how data science can be integrated to enhance efficiency and decision-making.

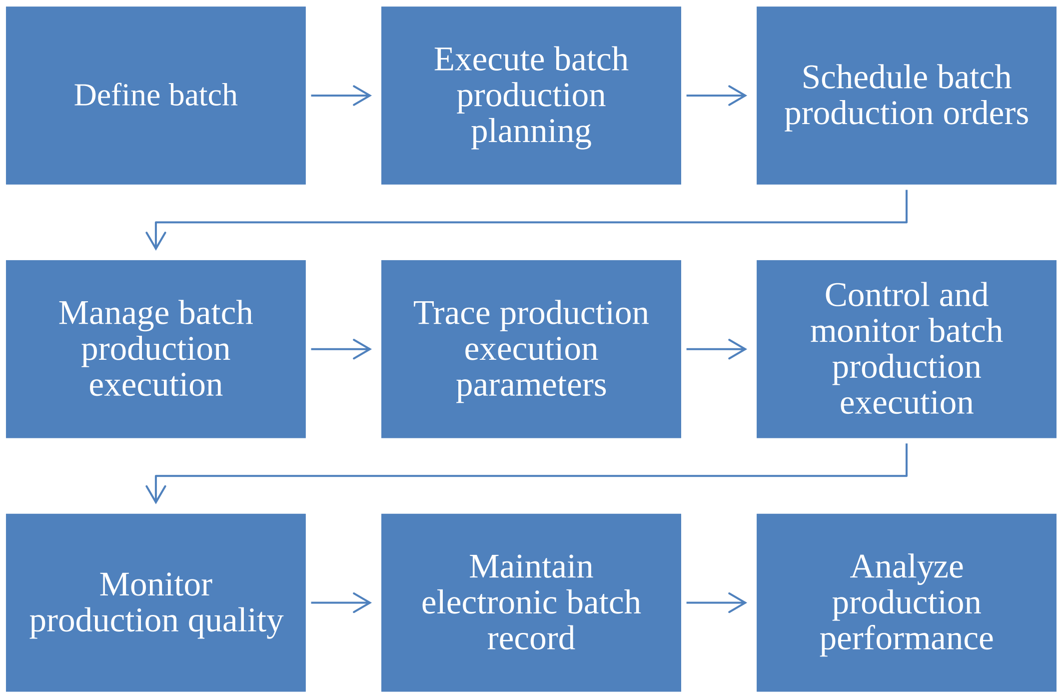

Figure 234 Typical Process in Batch Execution Control. Source: Author

Define Batch: This activity involves the specification and definition of a production batch. Data science can contribute by analyzing historical batch data, identifying patterns, and recommending optimal batch sizes and configurations to optimize production efficiency.

Execute Batch Production Planning: Data science plays a pivotal role in batch production planning by leveraging predictive modeling. It can analyze historical production data, resource availability, and market trends to optimize production plans, ensuring alignment with business goals and market demands.

Schedule Batch Production Orders: Scheduling batch production orders involves optimizing the allocation of resources and timelines. Data science can employ optimization algorithms to dynamically schedule production orders based on real-time factors, reducing turnaround times and resource wastage.

Manage Batch Production Execution: Efficient execution of batch production is facilitated by data science through real-time monitoring and adaptive control. Machine learning models can analyze production parameters, identify deviations, and dynamically adjust execution plans to ensure optimal outcomes.

Trace Production Execution Parameters: Data science contributes to traceability by implementing robust data tracking systems. This involves using technologies like RFID or IoT sensors to capture real-time production data, providing comprehensive traceability for each batch.

Control and Monitor Batch Production Execution: Data science-driven control systems enable real-time monitoring and control of batch production processes. Predictive analytics models can anticipate potential issues, allowing for proactive intervention to maintain quality and efficiency.

Monitor Production Quality: Monitoring production quality involves continuous analysis of quality parameters. Data science can implement quality prediction models to proactively identify potential quality issues, ensuring adherence to quality standards throughout the production process.

Maintain Electronic Batch Record: Maintaining electronic batch records is streamlined through data-driven record-keeping systems. Automation and analytics can ensure accuracy, completeness, and accessibility of electronic batch records, facilitating regulatory compliance and audits.

Analyze Production Performance: Data science-driven analytics are crucial for analyzing production performance. This involves employing machine learning algorithms to evaluate key performance indicators, identify improvement areas, and drive continuous optimization of production processes.

In summary, the integration of data science into the "Batch Execution Control" function enhances the entire lifecycle of batch production processes. From planning and execution to monitoring, traceability, and analysis, data science contributes to efficiency, quality, and adaptability. Furthermore, achieving business agility goals, such as improving behavioral and situational awareness, enabling inclusive and augmented decision-making, and creating dynamic processes and resources, is facilitated through the integration of AI-driven data science (Corbett & Mhaskar, 2016; Formentin et al., 2014; Natu & Sadaphal, 2015).

4.4.1.5 Process Batch Recipe Management

The function of "Process Batch Recipe Management" is integral in managing the formulation and execution of batch recipes within a manufacturing or production environment. This multifaceted function encompasses activities as shown in *Figure 235* ranging from introducing recipes for new products to managing trial batches. In this section, I will delve into the key activities performed by this function, highlighting how data science can enhance each process. Additionally, a subsequent section will explore how leveraging data science can achieve various business agility goals within this function.

Manage Introduction of Recipes for New Products: This activity involves the introduction of new recipes tailored to produce novel products. Data science can contribute by analyzing market trends, historical data, and customer preferences to suggest optimal formulations. Predictive modeling can assist in anticipating the success and viability of these new recipes.

Execute Transformation Rules: The execution of transformation rules involves the application of specified rules to convert raw materials into the final product. Data science plays a role by automating rule-based transformations through machine learning algorithms. This ensures consistency and accuracy in the execution process.

Manage Site-Specific Recipes: This activity deals with tailoring recipes to the specifics of each production site. Data science aids in analyzing site-specific variables, such as equipment capabilities and environmental conditions, to optimize recipes for each location, ensuring efficient and reliable production.

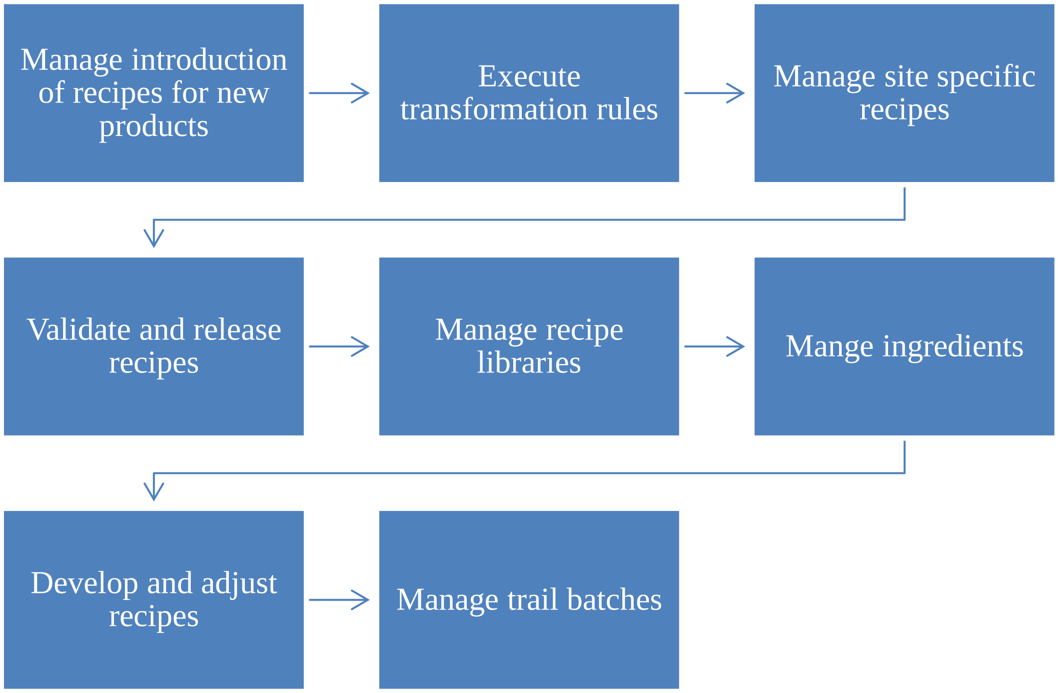

Figure 236 Typical Process of Process Batch Recipe Management. Source: Author

Validate and Release Recipes: Data science contributes to the validation and release of recipes by implementing automated quality control checks. Machine learning models can assess historical data to predict potential quality issues, ensuring that only validated and high-quality recipes are released for production.

Manage Recipe Libraries: This involves maintaining a comprehensive repository of recipes. Data science can enhance this process through automated categorization, tagging, and recommendation systems. Natural Language Processing (NLP) algorithms can extract insights from historical recipe data to optimize library management.

Manage Ingredients: Managing ingredients involves tracking and optimizing the availability and quality of raw materials. Data science can forecast ingredient requirements based on historical usage patterns, supplier performance, and market trends, ensuring a streamlined and efficient ingredient management process.

Develop and Adjust Recipes: Data science assists in the development and adjustment of recipes by analyzing feedback from production processes. Predictive analytics models can suggest modifications based on real-time data, optimizing recipes for improved quality and efficiency.

Manage Trial Batches: Trial batches are essential for testing new recipes or process adjustments. Data science contributes by analyzing trial batch data to assess performance, identify areas for improvement, and inform decisions on whether to scale up production.

In the intricate landscape of Process Batch Recipe Management, data science emerges as a transformative force. From refining recipe development to ensuring real-time awareness and enabling agile decision-making, data science stands as a catalyst for enhancing both operational efficiency and business agility. The integration of AI tools not only streamlines recipe-related processes but also cultivates a responsive and adaptable ecosystem, aligning with the dynamic requirements of modern manufacturing environments (Arzac-Garmendia et al., 2022; Poloski & Kantor, 2003; Romero et al., 2003).

4.4.1.6 Seamless Manufacturing Engineering

The function of Seamless Manufacturing Engineering encompasses various activities aimed at ensuring a smooth and efficient manufacturing process. This includes the ability to make real-time adjustments to Computer-Aided Manufacturing (CAM) programs, update part files, regenerate CAM programs, distribute NC programs to machine tools, and verify tool paths. This section provides an overview of each activity as shown in *Figure 237* and explores how data science can be leveraged to enhance these processes.

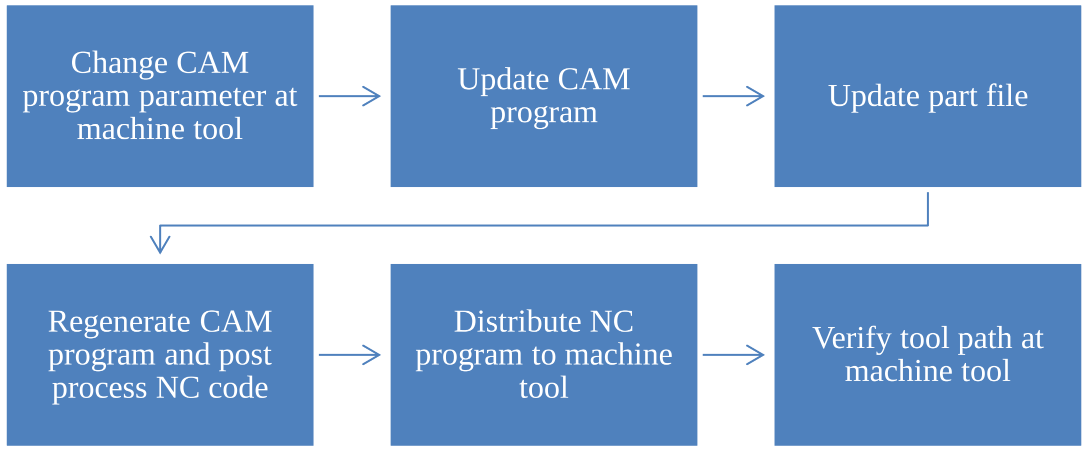

Figure 238 Typical Process in Seamless Manufacturing Engineering. Source: Author

Change CAM Program Parameter at Machine Tool: This involves adjusting parameters in the CAM program directly at the machine tool. Data science can optimize this process by analyzing historical parameter changes, predicting optimal adjustments, and providing recommendations for efficient CAM program modifications.

Update CAM Program: Updating CAM programs is crucial for incorporating design changes or process improvements. Data science can assist by automating the analysis of design modifications, suggesting corresponding changes in the CAM program, and ensuring the updated program aligns with manufacturing requirements.

Update Part File: Part files need updating to reflect design changes or revisions. Data science can streamline this process by automating the comparison between old and new designs, identifying differences, and generating updated part files efficiently.
Regenerate CAM Program and Post Process NC Code:

Regenerating CAM programs involves recalculating toolpaths based on design or parameter changes. Data science can optimize this process by predicting the impact of design alterations on toolpaths, automating the regeneration of CAM programs, and post-processing NC code for machine tool compatibility.

Distribute NC Program to Machine Tool: Distributing NC programs to machine tools ensures that the manufacturing process aligns with the latest program versions. Data science can enhance this activity by automating program distribution based on machine tool capabilities, optimizing scheduling for minimal downtime, and ensuring version control.

Verify Tool Path at Machine Tool: Verifying tool paths at the machine tool involves confirming that the programmed toolpaths align with the physical machining process. Data science can improve this process by employing computer vision algorithms for real-time verification, identifying discrepancies, and providing immediate feedback for adjustments.

In summary, Seamless Manufacturing Engineering involves a series of activities crucial for maintaining an efficient manufacturing process. By incorporating data science into these activities, organizations can achieve greater accuracy, efficiency, and responsiveness. Furthermore, leveraging data science for business agility goals enhances behavioral awareness, situational awareness, inclusive decision-making, augmented decision-making, dynamic processes, and dynamic resources in the Seamless Manufacturing Engineering function (Cattaneo et al., 2018; He et al., 2009; Kenett et al., 2018; Peres et al., 2017; Poloskei, 2021).

4.4.1.7 Shopfloor integrated resource management for PLM

The "Shopfloor Integrated Resource Management for PLM" function is pivotal in orchestrating a seamless and efficient production environment. This section explores the various activities as shown in *Figure 239* encompassed within this function and delves into the potential enhancements brought about by the integration of data science. Additionally, it addresses how data science can be harnessed to achieve specific business agility goals in this context.

Define Tool Master Data: Involves establishing a comprehensive repository of tool master data, encompassing specifications, usage parameters, and performance characteristics.

Data science facilitates the organization and analysis of this information, ensuring accurate and accessible tool data.

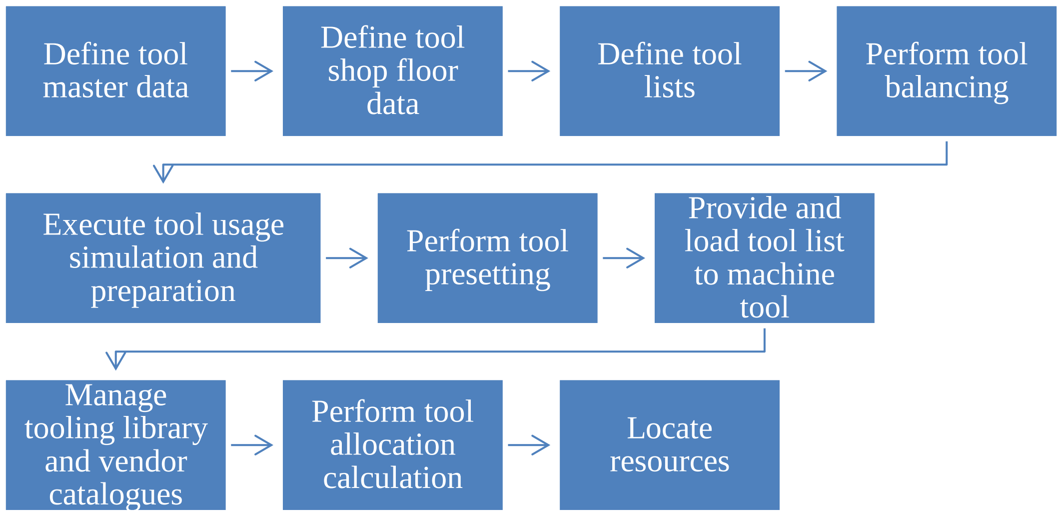

Figure 240 Typical Process in Shopfloor integrated resource management for PLM. Source: Author

Define Tool Shop Floor Data: Encompasses the definition of tool data specifically tailored for shop floor operations. Data science aids in optimizing this data by considering real-time operational constraints, tool wear patterns, and performance dynamics.

Define Tool Lists: Involves the creation and maintenance of lists detailing the tools required for specific manufacturing processes. Data science contributes by automating the generation of optimized tool lists based on historical usage patterns and real-time production demands.

Perform Tool Balancing: Entails the distribution of tools across machines to optimize workloads and prevent bottlenecks. Data science algorithms can analyze historical production data to predict optimal tool balancing strategies, ensuring efficient resource utilization.

Execute Tool Usage Simulation and Preparation: Involves simulating tool usage scenarios to identify potential issues and prepare for actual production. Data science aids in predictive modeling, allowing for realistic simulations that consider variables such as tool wear and machine capabilities.

Perform Tool Presetting: Encompasses configuring tools to predetermined specifications before usage. Data science contributes by automating tool presetting processes based on historical data, ensuring precision and efficiency.

Provide and Load Tool List to Machine Tool: Involves furnishing machine tools with the required tool lists for a specific production run. Data science optimizes this process by dynamically generating tool lists based on real-time production needs and resource availability.

Manage Tooling Library and Vendor Catalogues: Entails overseeing the tooling library and vendor catalogues, ensuring up-to-date and accurate information. Data science contributes by automating catalog management and recommending additions or modifications based on usage patterns.

Perform Tool Allocation Calculation: Involves calculating the optimal allocation of tools for specific tasks. Data science algorithms can analyze historical performance data to predict the most efficient tool allocations, minimizing production downtime.

Locate Resources: Entails identifying the physical location of tools and resources within the shop floor. Data science enhances this process by providing real-time tracking and visibility, reducing search times, and improving resource allocation.

In summary, the Shopfloor Integrated Resource Management for PLM function encompasses a range of activities crucial for efficient production operations. The integration of data science enhances these activities by providing predictive modeling, automation, and real-time analytics. Additionally, the incorporation of data science contributes to achieving specific business agility goals, improving behavioral awareness, situational awareness, inclusive decision-making, augmented decision-making, and creating dynamic processes and resources for fast execution on the shop floor (Gyulai et al., 2019; Ren et al., 2019; Srinivas & Harding, 2008; Urbina Coronado et al., 2018).

4.4.1.8 Mitigation Strategies for Challenges in Adoption of Data Science

In today's rapidly evolving manufacturing landscape, data science emerges as a critical enabler for operational efficiency and adaptability. *Table 34* delves into the multifaceted realm of Manufacturing Execution and Control, exploring how data science methodologies can revolutionize traditional processes. By scrutinizing tasks ranging from planning and scheduling to execution and resource management, uncover opportunities for leveraging artificial intelligence (AI) to streamline operations and align with overarching business agility objectives. However, this transformative journey is not without its challenges. From skill shortages to data quality concerns and integration complexities, organizations face formidable obstacles. Nevertheless, proactive mitigation strategies hold the promise of overcoming these hurdles, fostering a collaborative environment conducive to innovation and sustainable growth.

Table 34 Data Science Use Cases for the various process in Manufacturing Execution Management and Control. Source: Author

Process	**Data Science Use Cases**	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Manufacturing Planning and Scheduling	Predictive modeling for demand forecasting	Improve Situational Awareness, Enable Augmented Decision Making	Lack of skilled workforce, Data quality and availability, Integration	Inefficient production planning, Inaccurate decision-making,	Invest in training programs, implement data quality checks, Collaborate

Table 34 Data Science Use Cases for the various process in Manufacturing Execution Management and Control. Source: Author					
Process	**Data Science Use Cases**	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
			with existing systems	System incompatibility	with IT for seamless integration
Manufacturing Order Execution	Real-time production monitoring and analytics	Improve Situational Awareness, Enable Augmented Decision Making	Lack of skilled workforce, Data quality and availability, Integration with existing systems	Inefficient production processes, Inaccurate decision-making, System incompatibility	Invest in training programs, implement data quality checks, Collaborate with IT for seamless integration
Electronics Manufacturing Order Execution	Machine learning for defect detection and prevention	Improve Situational Awareness, Enable Augmented Decision Making	Lack of skilled workforce, Data quality and availability, Privacy and security concerns, Integration	Production delays and defects, Data breaches and leaks, Inaccurate decision-making	Invest in training programs, implement data encryption measures, Collaborate with IT for

Table 34 Data Science Use Cases for the various process in Manufacturing Execution Management and Control. Source: Author					
Process	**Data Science Use Cases**	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
			with existing systems		secure integration
Batch Execution Control	Predictive maintenance for batch equipment	Improve Situational Awareness, Enable Augmented Decision Making	Lack of skilled workforce, Data quality and availability, Integration with existing systems	Equipment breakdowns and downtime, Inaccurate decision-making, System incompatibility	Invest in training programs, implement data quality checks, Collaborate with IT for seamless integration
Process Batch Recipe Management	AI-driven recipe optimization and adjustment	Improve Situational Awareness, Enable Augmented Decision Making	Lack of skilled workforce, Data quality and availability, Integration with existing systems	Inefficient recipe management, Inaccurate decision-making, System incompatibility	Invest in training programs, implement data quality checks, Collaborate with IT for seamless integration

Table 34 Data Science Use Cases for the various process in Manufacturing Execution Management and Control. Source: Author					
Process	**Data Science Use Cases**	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Seamless Manufacturing Engineering	Machine learning for CNC program optimization	Improve Situational Awareness, Enable Augmented Decision Making	Lack of skilled workforce, Data quality and availability, Integration with existing systems	Inefficient machining processes, Inaccurate decision-making, System incompatibility	Invest in training programs, implement data quality checks, Collaborate with IT for seamless integration
Shopfloor Integrated Resource Management	AI-driven resource allocation and optimization	Improve Situational Awareness, Enable Augmented Decision Making	Lack of skilled workforce, Data quality and availability, Integration with existing systems	Inefficient resource utilization, Inaccurate decision-making, System incompatibility	Invest in training programs, implement data quality checks, Collaborate with IT for seamless integration

Through a comprehensive understanding of data science use cases and strategic approaches to address challenges, manufacturing enterprises can embark on a transformative journey towards enhanced efficiency, resilience, and competitiveness in the digital age.

In conclusion, the integration of data science into Manufacturing Execution and Control functions offers immense potential for driving operational excellence and achieving business agility. By harnessing AI-driven insights, organizations can optimize production processes, enhance decision-making capabilities, and adapt swiftly to changing market demands. However, realizing these benefits requires overcoming challenges such as skill shortages, data quality issues, and system integration complexities. Through strategic investments in training, data governance, and collaborative efforts across departments, organizations can mitigate these risks and unlock the full potential of data science to drive innovation and competitiveness in the manufacturing industry.

4.4.2 Mitigation Strategies for Challenges in Adoption of Data Science in Shop Floor Logistics

In the realm of Shop Floor Logistics within a Manufacturing Execution function, data science plays a pivotal role in enhancing various business processes. This section discusses the different data science use cases in this domain and its sub activities as shown in *Figure 241*, associated challenges and risk along with the proposed mitigation strategies that can be taken by organizations.

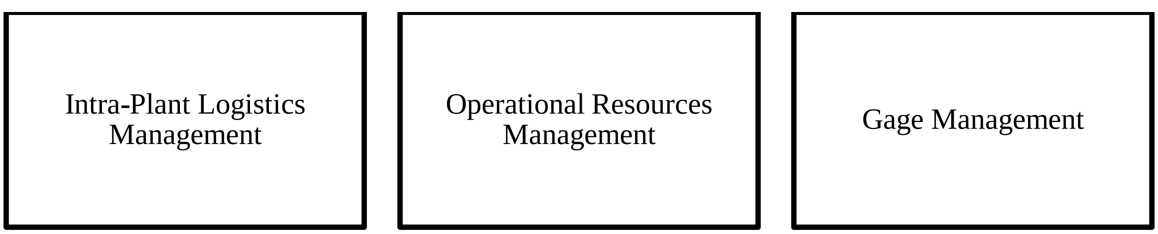

Figure 242 Typical Sub Functions in Shop Floor Logistics. Source: Author

In essence, the integration of data science into Shop Floor Logistics within a Manufacturing Execution function not only enhances specific sub-functions but also contributes to a more agile, adaptive, and efficient manufacturing ecosystem. By harnessing the power of data-driven insights, organizations can navigate the complexities of modern manufacturing with increased precision, resilience, and competitiveness (Farooqui et al., 2019; Flath & Stein, 2018; Gyulai et al., 2019; Stein & Flath, 2017; Urbina et al., 2018).

4.4.2.1 Intra-Plant Logistics Management

Intra-Plant Logistics Management is a pivotal function within the broader spectrum of supply chain and material management. This function encompasses a range of activities as shown in *Figure 243* which are critical for efficient material flow within a manufacturing plant. This section delves into the various activities involved and explores how data science can enhance the performance of these functions.

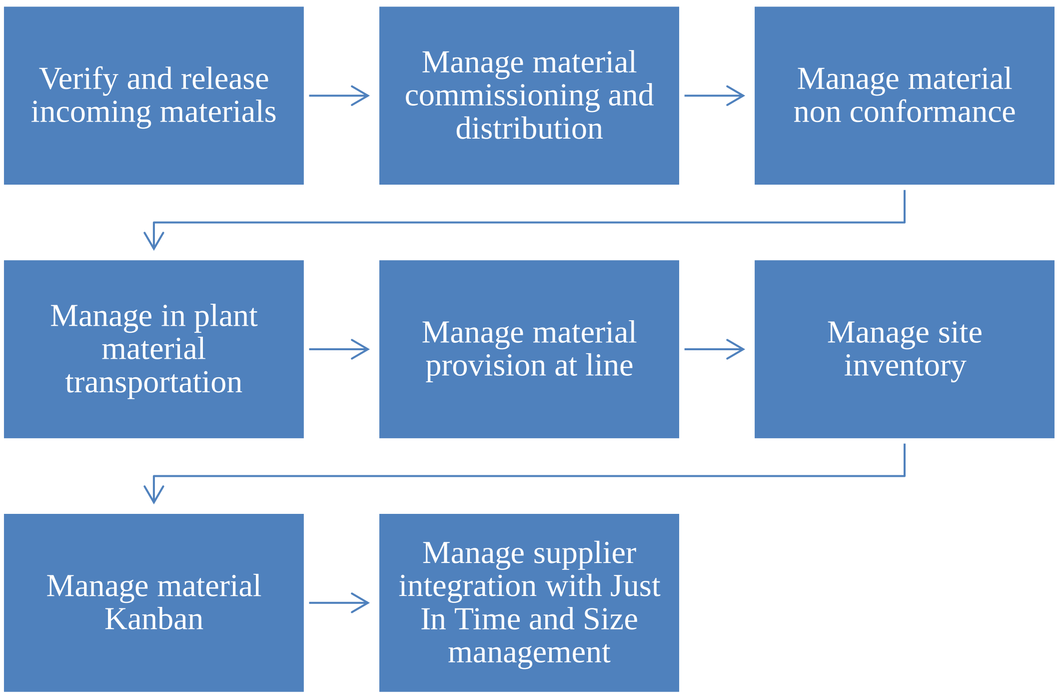

Figure 244 Typical Process Flow of Intra-Plant Logistics Management. Source: Author

Verify and Release Incoming Materials: This involves the validation and release of incoming materials. Data science can be applied to automate the verification process by utilizing image recognition, RFID technology, or other sensor data to ensure accurate and timely validation of incoming materials.

Manage Material Commissioning and Distribution: This activity focuses on the organized commissioning and distribution of materials within the plant. Data science facilitates optimization of distribution routes, inventory levels, and commissioning processes, ensuring a streamlined and efficient material flow.

Manage Material Non-Conformance: In the event of material non-conformance, data science can contribute by implementing anomaly detection algorithms to identify deviations in material specifications. This enables swift corrective actions and minimizes disruptions.

Manage In-Plant Material Transportation: Efficient transportation within the plant is crucial. Data science can optimize material transportation routes, considering real-time data on demand, production schedules, and facility conditions.

Manage Material Provision at Line: This involves ensuring that materials are provisioned efficiently at production lines. Predictive analytics can forecast material requirements, preventing shortages, and optimizing the provisioning process.

Manage Site Inventory: Data science plays a vital role in inventory management by implementing predictive models for demand forecasting, ensuring optimal stock levels, and minimizing excess inventory costs.

Manage Material Kanban: Kanban systems rely on real-time information. Data science can enhance Kanban systems by providing real-time visibility into material usage patterns, enabling proactive adjustments to Kanban signals.

Manage Supplier Integration with Just In Time and Size Management: Data science can facilitate seamless integration with suppliers by applying Just In Time (JIT) principles. Predictive analytics can optimize order quantities, reducing excess inventory. Size management can be enhanced by analyzing historical data to determine optimal order sizes based on demand patterns.

In conclusion, Intra-Plant Logistics Management, supported by data science, becomes a dynamic and responsive function within the supply chain. From verifying incoming materials to enhancing business agility through AI-driven insights, the integration of data science optimizes processes, fosters efficient material flow, and ensures a heightened level of adaptability within the manufacturing plant (Burggraf et al., 2018; Detwal et al., 2023; Gocebe et al., 2015; Härtel & Nyhuis, 2019; Pujiarto, 2021).

4.4.2.2 Operational Resources Management

The Operational Resources Management function is crucial within the broader scope of supply chain and material management, encompassing activities related to the efficient handling and utilization of operational resources. This section delves into the key responsibilities of this function as shown in *Figure 245* and explores how data science can be applied to enhance each activity. Subsequently, the discussion shifts to how the implementation of data science can improve business agility in Operational Resources Management.

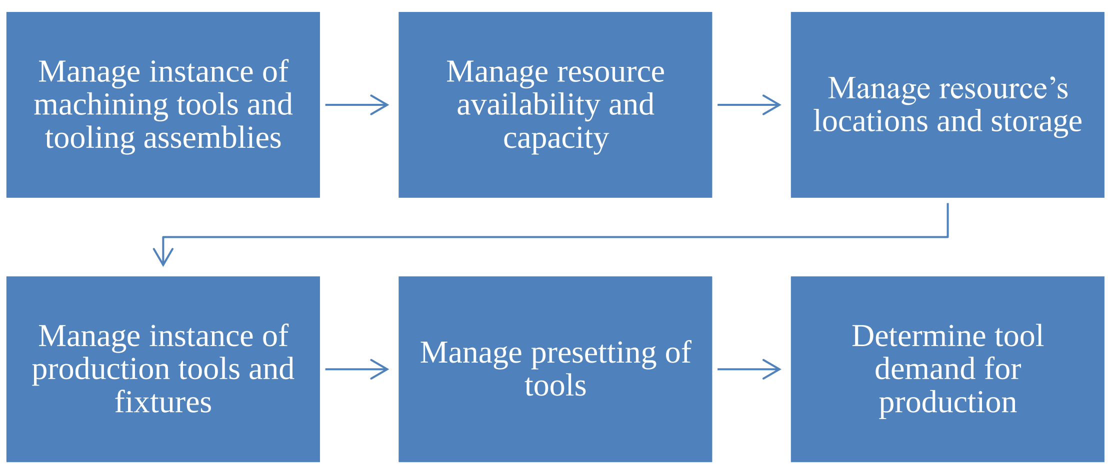

Figure 246 Typical Process Flow of Operational Resources Management. Source: Author

Manage Instances of Machining Tools and Tooling Assemblies: Efficient management of machining tools and tooling assemblies involves tracking their usage, maintenance schedules, and performance. Data science can contribute by implementing predictive maintenance models, analyzing historical tool performance to anticipate potential failures, and optimizing tool allocation based on real-time demand.

Manage Resource Availability and Capacity: Data science plays a vital role in resource availability and capacity management by analyzing historical usage patterns and predicting future demand. Machine learning algorithms can optimize resource allocation, ensuring that capacity meets demand while minimizing idle resources.

Manage Resource's Locations and Storage: Data science enhances location and storage management by optimizing warehouse layouts, minimizing travel times, and ensuring efficient resource retrieval. Predictive analytics can forecast optimal storage locations based on usage patterns and real-time demand, optimizing the overall storage layout.

Manage Instances of Production Tools and Fixtures: Effective management of production tools and fixtures involves tracking usage, maintenance, and performance. Data science applications can predict maintenance needs, optimize tool usage based on production schedules, and automate the allocation of fixtures to enhance overall production efficiency.

Manage Presetting of Tools: Data science can contribute to tool presetting management by automating the process based on historical tool usage data. Machine learning algorithms can optimize tool presetting parameters, ensuring that tools are calibrated precisely for specific production requirements.

Determine Tool Demand for Production: Predicting tool demand is critical for ensuring that production processes have the necessary tools available. Data science applications can analyze production schedules, historical tool demand patterns, and real-time production conditions to accurately forecast tool requirements.

In conclusion, the Operational Resources Management function, vital within supply chain and material management, benefits significantly from the integration of data science. Leveraging predictive analytics, machine learning, and AI-driven insights, this function can optimize tool and resource management, enhance decision-making, and improve overall business agility. The implementation of data science contributes to a more efficient, responsive, and adaptable Operational Resources Management system within the broader supply chain framework (Hu et al., 2022; Kumar et al., 2013; Mišić & Perakis, 2020; Walker et al., 2022; Yu et al., 2011).

4.4.2.3 Industrial Measuring Gage Management

The function of Industrial Measuring Gage Management is integral to ensuring precision and accuracy in manufacturing processes. This section delves into the multifaceted activities encompassed by this function as shown in *Figure 247*, including managing new gage introductions, handling specification revisions, asset identification, calibration label printing, global support, calibration reporting, equipment performance monitoring, external metrology labs management, gage management reporting, and recalibration recalls. Additionally, this section explores how the integration of data science can enhance these activities, followed by a discussion on achieving business agility goals using data science.

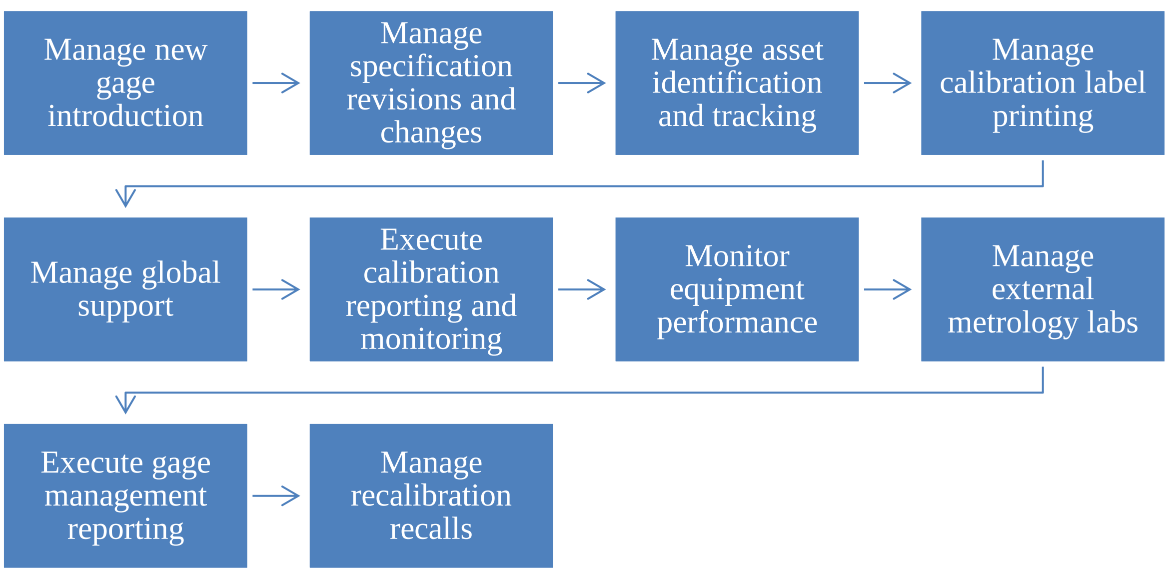

Figure 248 Typical Process Flow of Industrial Measuring Gage Management. Source: Author

Manage New Gage Introduction: This involves the systematic introduction of new measuring gauges into the system. Data science can streamline this process by analyzing historical data to identify optimal introduction methods, reducing lead times, and improving overall efficiency.

Manage Specification Revisions and Changes: Handling revisions and changes to specifications requires meticulous tracking and analysis. Data science contributes by automating the detection of changes, ensuring prompt updates, and minimizing the risk of using outdated specifications.

Manage Asset Identification and Tracking: Efficient asset identification and tracking are crucial for traceability. Data science technologies such as RFID and barcode systems enhance tracking accuracy, providing real-time insights into the location and status of measuring gauges.

Manage Calibration Label Printing: Data science streamlines calibration label printing by automating the process based on predefined calibration schedules. This reduces manual effort and ensures that labels accurately reflect the calibration status of each gage.

Manage Global Support: Ensuring global support for measuring gauges involves analyzing data to anticipate and address potential issues. Data science-driven predictive analytics can identify patterns and proactively recommend support measures, reducing downtime and enhancing global operations.

Execute Calibration Reporting and Monitoring: Calibration reporting and monitoring involves analyzing calibration data for compliance and accuracy. Data science facilitates this by automating the generation of reports and continuously monitoring calibration metrics to identify deviations and trigger corrective actions.

Monitor Equipment Performance: Data science plays a pivotal role in monitoring equipment performance by analyzing real-time data from measuring gauges. Predictive maintenance models can anticipate potential issues, allowing for proactive maintenance and minimizing downtime.

Manage External Metrology Labs: Coordinating with external metrology labs requires effective data exchange. Data science ensures seamless collaboration by optimizing data integration and automating communication processes, leading to more efficient external partnerships.

Execute Gage Management Reporting: Gage management reporting involves synthesizing data for comprehensive insights. Data science-driven analytics tools can process large datasets, providing detailed reports on gage status, performance, and compliance.

Manage Recalibration Recalls: Efficient recalibration recalls involve analyzing data to identify gauges due for recalibration. Data science automates this process by setting up intelligent recall triggers based on usage patterns and calibration history.

In conclusion, Industrial Measuring Gage Management is a complex function vital to ensuring accuracy in manufacturing processes. The integration of data science enhances various activities, from introducing new gauges to managing recalibration recalls. Additionally, by leveraging data science to achieve business agility goals, organizations can improve behavioral awareness, situational awareness, inclusive decision-making, augmented decision-making, and create dynamic processes and resources for fast execution in gage management processes. This comprehensive approach ensures precision, efficiency, and agility in the management of industrial measuring gauges within the broader context of supply chain collaboration and material management (Jia et al., 2014; Liu et al., 2018; Montazeri et al., 2019; Solomakhina et al., 2014; Vanden et al., 2021).

4.4.2.4 Mitigation Strategies for Challenges in Adoption of Data Science

In the realm of Manufacturing Execution and Operations, the Shop Floor Logistics function plays a pivotal role in ensuring the seamless flow of materials and resources throughout the production process. Leveraging data science methodologies, organizations can optimize various aspects of logistics management, from intra-plant material handling to resource allocation and industrial equipment management. By harnessing AI-driven predictive maintenance, demand forecasting, and route optimization, businesses can enhance behavioural and situational awareness, enabling more inclusive and augmented decision-making processes. However, implementing data science solutions poses several challenges, including skill shortages, data quality issues, and integration complexities. To mitigate these risks, organizations must invest in comprehensive training programs, data validation processes, and robust security measures, ensuring alignment with overarching business objectives.

Intra-Plant Logistics Management involves the efficient handling and movement of materials within a manufacturing facility. This includes tasks such as verifying incoming materials, managing material distribution, and maintaining inventory levels. By optimizing intra-plant logistics, organizations can streamline production processes, reduce lead times, and minimize costs associated with material handling and storage. Leveraging data science techniques such as predictive maintenance, demand forecasting, and route optimization can further enhance the effectiveness of intra-plant logistics operations, leading to improved productivity and responsiveness to changing production demands. Table 35 summarizes the different data science use cases in this domain, associated challenges and risk along with the proposed mitigation strategies that can be taken by organizations.

Table 35 Data Science Use Cases for the various process in Shop Floor Logistics - Intra-Plant Logistics Management. Source: Author

Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Predictive maintenance	Improve Behavioral Awareness	Lack of skilled workforce	Delayed maintenance and breakdowns	Provide comprehensive training programs and invest in upskilling initiatives.

Table 35 Data Science Use Cases for the various process in Shop Floor Logistics - Intra-Plant Logistics Management. Source: Author

Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Demand forecasting	Improve Situational Awareness	Data quality and availability	Inaccurate forecasts and decisions	Implement data validation processes and invest in data quality improvement initiatives.
Route optimization	Enable Inclusive decision making	Integration with existing systems	Inefficient workflows and errors	Utilize interoperable platforms and APIs for seamless integration with existing systems.
Inventory optimization	Enable augmented decision making	Privacy and security concerns	Data breaches and unauthorized access	Implement robust data encryption protocols and access controls to safeguard sensitive information.
Inventory optimization	Create dynamic processes for fast execution	Scalability	Limited scalability and performance issues	Implement scalable infrastructure and utilize cloud-based solutions for elasticity and flexibility.

Table 35 Data Science Use Cases for the various process in Shop Floor Logistics - Intra-Plant Logistics Management. Source: Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Inventory optimization	Create dynamic resources for fast execution	Alignment with business objectives	Misaligned strategies and goals	Align data science initiatives with overarching business objectives and priorities.

Operational Resources Management ensures optimal utilization and availability of machining tools, production resources, and fixtures. Leveraging data science for predictive maintenance and real-time monitoring enhances resource efficiency and reduces downtime. By integrating with existing systems, such as ERP and MES, decision-making becomes more agile and informed. However, challenges like scalability and data quality need mitigation through standardized processes and skilled workforce training. Overall, data-driven insights facilitate dynamic resource allocation, aligning operations with business objectives for improved productivity and competitiveness. Table 36 summarizes the different data science use cases in this domain, associated challenges and risk along with the proposed mitigation strategies that can be taken by organizations.

Table 36 Data Science Use Cases for the various process in Shop Floor Logistics - Operational Resources Management. Source: Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Predictive maintenance	Improve Behavioral Awareness	Lack of skilled workforce	Delayed maintenance and breakdowns	Provide comprehensive training programs and invest in upskilling initiatives.

Table 36 Data Science Use Cases for the various process in Shop Floor Logistics - Operational Resources Management. Source: Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Resource allocation optimization	Improve Situational Awareness	Data quality and availability	Inaccurate forecasts and decisions	Implement data validation processes and invest in data quality improvement initiatives.
Predictive tool availability	Enable Inclusive decision making	Integration with existing systems	Inefficient workflows and errors	Utilize interoperable platforms and APIs for seamless integration with existing systems.
Predictive tool availability	Enable augmented decision making	Privacy and security concerns	Data breaches and unauthorized access	Implement robust data encryption protocols and access controls to safeguard sensitive information.
Predictive tool availability	Create dynamic processes for fast execution	Scalability	Limited scalability and performance issues	Implement scalable infrastructure and utilize cloud-based solutions for elasticity and flexibility.
Predictive tool availability	Create dynamic resources for fast execution	Alignment with business objectives	Misaligned strategies and goals	Align data science initiatives with overarching business objectives and priorities.

Industrial Measuring Gage Management ensures accurate measurement tools for quality control. It involves introducing, tracking, and calibrating gauges while monitoring performance. Leveraging data science, such as predictive maintenance and anomaly detection, enhances gauge reliability and efficiency. Challenges include skilled workforce shortages, data quality assurance, and integration complexities, mitigated through training, data validation protocols, and system integration strategies. This process aligns with business agility goals by improving situational awareness and facilitating augmented decision-making through real-time data insights. Table 37 summarizes the different data science use cases in this domain, associated challenges and risk along with the proposed mitigation strategies that can be taken by organizations.

Table 37 Data Science Use Cases for the various process in Shop Floor Logistics - Industrial Measuring Gage Management. Source: Author

Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Predictive maintenance	Improve Behavioral Awareness	Lack of skilled workforce	Delayed maintenance and breakdowns	Provide comprehensive training programs and invest in upskilling initiatives.
Anomaly detection	Improve Situational Awareness	Data quality and availability	Inaccurate forecasts and decisions	Implement data validation processes and invest in data quality improvement initiatives.
Predictive calibration scheduling	Enable Inclusive decision making	Integration with existing systems	Inefficient workflows and errors	Utilize interoperable platforms and APIs for seamless

Table 37 Data Science Use Cases for the various process in Shop Floor Logistics - Industrial Measuring Gage Management. Source: Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
				integration with existing systems.
Predictive calibration scheduling	Enable augmented decision making	Privacy and security concerns	Data breaches and unauthorized access	Implement robust data encryption protocols and access controls to safeguard sensitive information.
Predictive calibration scheduling	Create dynamic processes for fast execution	Scalability	Limited scalability and performance issues	Implement scalable infrastructure and utilize cloud-based solutions for elasticity and flexibility.
Predictive calibration scheduling	Create dynamic resources for fast execution	Alignment with business objectives	Misaligned strategies and goals	Align data science initiatives with overarching business objectives and priorities.

In conclusion, the integration of data science into Shop Floor Logistics offers immense potential for improving operational efficiency and agility in manufacturing environments. By addressing challenges related to workforce skills, data quality, and system integration, organizations can unlock the full benefits of Data Science -driven solutions. Through proactive mitigation strategies and a strong alignment with business objectives, companies can navigate the complexities of data science implementation and pave the way for a more dynamic and resilient manufacturing ecosystem.

4.4.3 Mitigation Strategies for Challenges in Adoption of Data Science in Industrial Production Monitoring and Analytics

In the realm of Industrial Production Monitoring and Analytics within a Manufacturing Execution function, the integration of data science methodologies has become paramount for enhancing efficiency, improving quality, and optimizing overall production processes. This section explores several key sub-functions as shown in Figure 134 and illustrates how data science can be instrumental in each area.

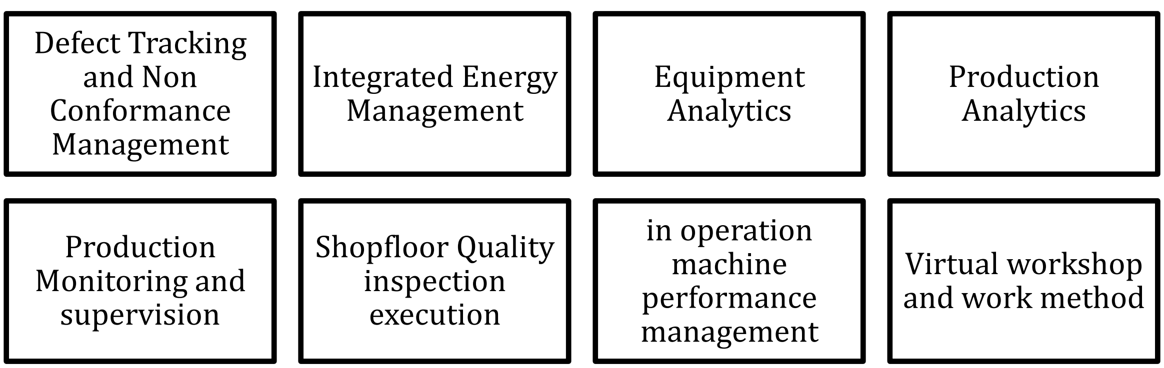

Figure 249 Typical Sub Functions of Industrial Production Monitoring and Analytics. Source: Author

The integration of data science into these sub-functions not only addresses immediate challenges but also establishes a foundation for continuous improvement. By harnessing the power of data, manufacturing enterprises can foster innovation, increase competitiveness, and adapt to the dynamic demands of the industry. This data-centric approach transforms industrial production monitoring and analytics from a reactive process to a proactive, strategic driver of operational success (Fang et al., 2020; Flath & Stein, 2018; Klaeger et al., 2021; Sadati et al., 2018; Shang & You, 2019; Wu et al., 2018; Wu et al., 2017).

4.4.3.1 Defect Tracking and Non-Conformance Management

Within the realm of supply chain and material management, the function responsible for "Defect Tracking and Non-Conformance Management" plays a crucial role in ensuring product quality and adherence to standards. This section delves into the activities encompassed by this function as shown in *Figure 250*, highlighting how data science can enhance each facet of defect tracking and non-conformance management.

Declare and Track Production Issues: This involves the identification and documentation of any deviations or defects in the production process. Data science can enhance this activity by implementing automated tracking systems that analyze real-time data to swiftly identify and log production issues, ensuring a proactive approach to problem-solving.

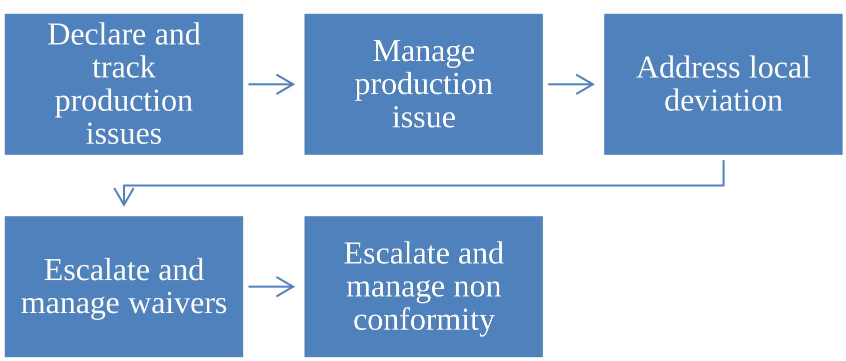

Figure 251 Process Flow of Defect Tracking and Non-Conformance Management. Source: Author

Manage Production Issues: This activity revolves around coordinating efforts to address and resolve identified production issues. Data science can contribute by analyzing historical data on issue resolutions, predicting potential bottlenecks, and recommending optimized strategies for efficient production issue management.

Address Local Deviation: Local deviations refer to specific instances where the production process deviates from the standard procedures. Data science can aid in addressing local deviations by providing real-time insights into the root causes, enabling quick corrective actions, and preventing widespread disruptions.

Escalate and Manage Waivers: In cases where deviations are intentional and require approval, data science can automate the analysis of waiver requests. By assessing the impact of proposed waivers on overall quality and compliance, data-driven decision-making ensures that waivers are managed efficiently while minimizing risks.

Escalate and Manage Non-Conformity: Non-conformities represent systemic issues that may require broader interventions. Data science can facilitate this activity by analyzing patterns in non-conformities, identifying systemic root causes, and recommending strategic interventions to prevent recurrence and enhance overall conformity.

In conclusion, the integration of data science into the Defect Tracking and Non-Conformance Management function within supply chain and material management offers a comprehensive and agile approach. By utilizing AI-driven analytics, organizations can achieve heightened behavioral and situational awareness, foster inclusive and augmented decision-making, and create dynamic processes and resource allocations for swift execution. This data-centric approach ensures a proactive and efficient response to production issues, deviations, and non-conformities, ultimately enhancing the overall quality and compliance of the entire value chain (Aqlan et al., 2017; Bártová et al., 2022; Caglayan et al., 2010; Chan et al., 2017; Prakash et al., 2015).

4.4.3.2 Integrated Energy Management

Integrated Energy Management is a pivotal function within organizations, responsible for overseeing and optimizing energy-related activities. This multifaceted function as shown in *Figure 252* involves monitoring energy consumption, analyzing energy data, performing energy efficiency control, optimizing energy consumption, and optimizing energy procurement and prognosis.

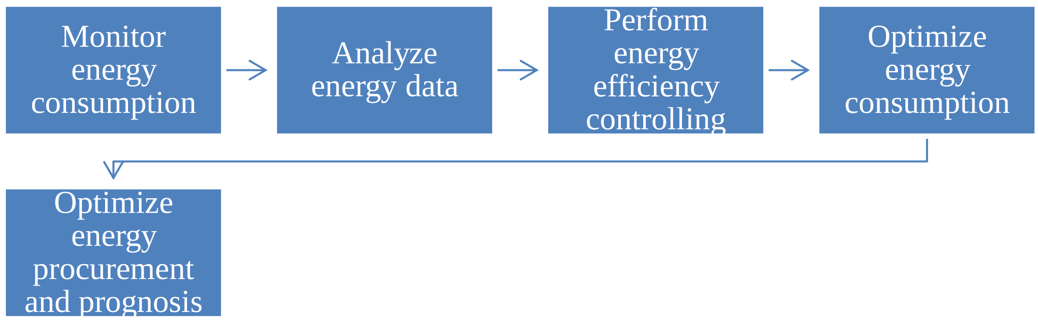

Figure 253 Typical Process Flow of Integrated Energy Management. Source: Author

The integration of data science into these activities enhances efficiency, decision-making, and overall business agility.

Monitoring Energy Consumption: Monitoring energy consumption involves tracking the usage of energy resources in real-time. Data science contributes by employing IoT sensors and data analytics to collect and process energy consumption data. Machine learning algorithms can identify patterns, anomalies, and trends, providing insights into usage patterns and potential areas for optimization.

Analyzing Energy Data: Data science plays a crucial role in analyzing energy data through advanced analytics techniques. Predictive modeling, regression analysis, and clustering algorithms can uncover hidden patterns, forecast future energy needs, and identify factors influencing consumption. This analysis supports informed decision-making and proactive energy management strategies.

Performing Energy Efficiency Controlling: Energy efficiency controlling involves implementing measures to optimize energy use. Data science contributes by developing control algorithms that adjust energy systems based on real-time data. Machine learning models can dynamically adapt to changing conditions, ensuring continuous optimization and energy efficiency.

Optimizing Energy Consumption: Optimizing energy consumption utilizes data science to identify areas for improvement and implement strategies for efficiency. Machine learning algorithms can analyze historical consumption data, predict optimal consumption levels, and recommend adjustments to operations or equipment to minimize waste and enhance overall efficiency.

Optimizing Energy Procurement and Prognosis: Data science is instrumental in optimizing energy procurement and prognosis. Predictive analytics models can assess market conditions, forecast energy prices, and recommend optimal procurement strategies. This proactive approach ensures cost-effectiveness and reliability in energy procurement.

In summary, Integrated Energy Management, supported by data science, encompasses activities ranging from real-time monitoring to predictive optimization. The integration of AI enhances behavioral and situational awareness, enables inclusive and augmented decision-making, and creates dynamic processes and resource allocation for improved business agility. This synergy between Integrated Energy Management and data science lays the foundation for a responsive, efficient, and adaptable approach to energy-related challenges within organizations (Cannata et al., 2009; Delgado-Gomes et al., 2016; Kumar et al., 2021; Macheso et al., 2021; May et al., 2013; Molina-Solana et al., 2017; Tan et al., 2017).

4.4.3.3 Equipment Analytics

The Equipment Analytics function plays a pivotal role in modern industries by harnessing data to optimize equipment performance, streamline maintenance processes, and enhance overall operational efficiency. This section delves into the key activities of the Equipment Analytics function as shown in *Figure 254*, exploring how data science is applied to perform data acquisition and logging, analyze machine operation performance, run performance comparisons and optimizations, plan, execute, and monitor maintenance agreements, and manage alerts, escalations, and maintenance actions.

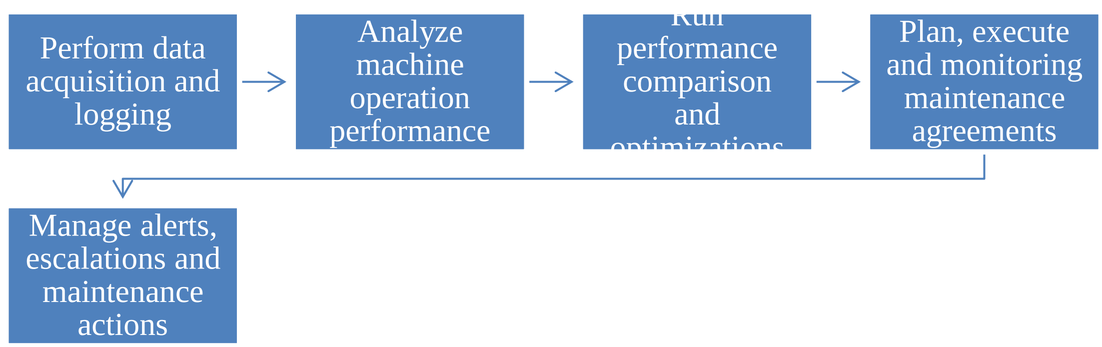

Figure 255 Typical Process Flow of Equipment Analytics. Source: Author

Perform Data Acquisition and Logging: This activity involves collecting and storing data from various equipment sources. Data science is applied to design efficient data acquisition systems, ensuring the capture of relevant operational parameters. Machine learning algorithms can preprocess and log this data, facilitating subsequent analyses.

Analyze Machine Operation Performance: Data science enables the analysis of machine operation data to assess performance metrics. Machine learning models can identify patterns, anomalies, and potential areas for improvement. This analysis provides insights into machine health, efficiency, and overall operational effectiveness.

Run Performance Comparison and Optimizations: Comparing equipment performance over time is essential for identifying trends and areas of inefficiency. Data science facilitates performance comparisons by leveraging statistical analysis and machine learning algorithms. Optimization algorithms can then recommend adjustments to enhance overall equipment efficiency.

Plan, Execute, and Monitor Maintenance Agreements: Data science plays a critical role in planning and executing maintenance activities. Predictive analytics models can forecast equipment maintenance needs based on historical performance data, optimizing maintenance schedules. Machine learning algorithms monitor ongoing maintenance agreements, providing real-time insights and ensuring compliance.

Manage Alerts, Escalations, and Maintenance Actions: Efficient management of alerts and escalations is vital for addressing potential issues promptly. Data science is employed to develop intelligent alert systems, utilizing anomaly detection algorithms. Automated workflows powered by machine learning can recommend and prioritize maintenance actions, ensuring a proactive and responsive approach.

In summary, the Equipment Analytics function, empowered by data science, plays a crucial role in optimizing equipment performance and maintenance processes. By applying AI tools, this function achieves business agility goals, improving behavioral and situational awareness, enabling inclusive and augmented decision-making, and creating dynamic processes and resources for fast execution within the ever-evolving operational landscape (Dagnino & Cox, 2014; Flath & Stein, 2018; Khan et al., 2017; Koester, 2019; Naumov et al., 2018; O'Donovan et al., 2015; Ahmad, 2020).

4.4.3.4 Production Analytics

The Production Analytics function plays a pivotal role in optimizing manufacturing operations, ensuring efficiency, and fostering continuous improvement. This section delves into the activities performed by this function as shown in *Figure 256* and explores how data science can be leveraged to enhance each of these activities. Additionally, a dedicated segment discusses how data science contributes to achieving various business agility goals within the Production Analytics function.

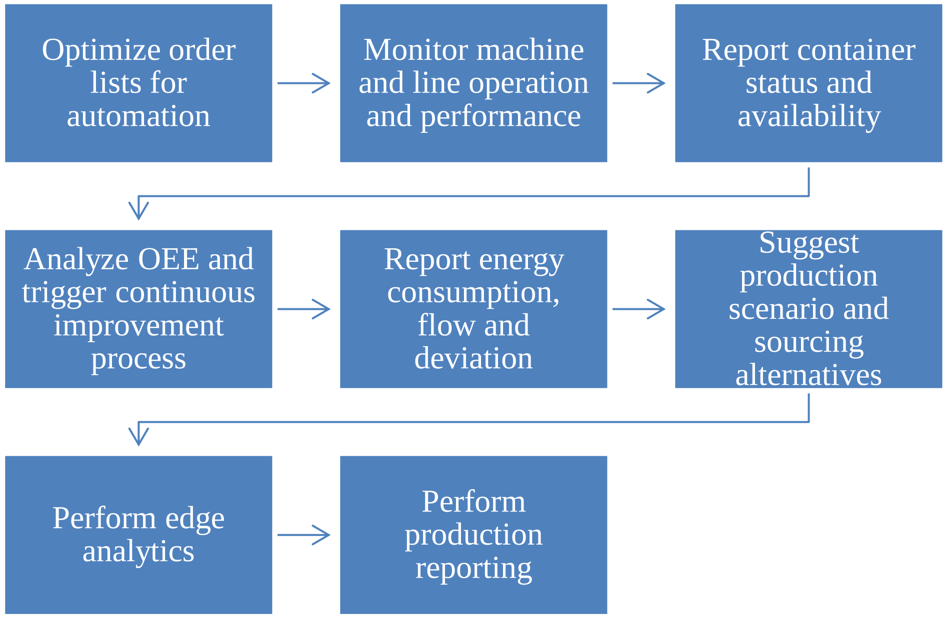

Figure 257 Typical Process Flow of Production Analytics. Source: Author

Optimize Order Lists for Automation: Production Analytics involves utilizing data science to optimize order lists for automation. Machine learning algorithms can analyze historical order data, production capacity, and resource availability to generate optimized order lists, maximizing the efficiency of automated production processes.

Monitor Machine and Line Operation and Performance: Data science enables real-time monitoring of machine and production line operations. Through sensors and IoT devices, machine learning algorithms can analyze operational data, detect anomalies, and predict potential failures, allowing for proactive maintenance and performance optimization.

Report Container Status and Availability: Utilizing data science, container status and availability can be accurately reported. RFID technology and sensor data can be analyzed to track container movements, assess availability, and provide real-time status reports, ensuring streamlined production processes.

Analyze OEE and Trigger Continuous Improvement Process: Data science is instrumental in analyzing Overall Equipment Effectiveness (OEE). Machine learning models can assess

OEE metrics, identify inefficiencies, and trigger a continuous improvement process by providing actionable insights to enhance overall equipment performance.

Report Energy Consumption, Flow, and Deviation: Production Analytics involves reporting on energy consumption, flow, and deviation. Data science utilizes analytics to monitor energy usage, assess production flow, and detect deviations from optimal conditions, enabling informed decision-making for resource optimization.

Suggest Production Scenario and Sourcing Alternatives: Machine learning algorithms can suggest optimal production scenarios and sourcing alternatives. By analyzing historical production data, market trends, and supplier performance, data science supports decision-making for efficient production planning and sourcing strategies.

Perform Edge Analytics: Edge analytics is executed to process data locally at the source. Data science enables edge analytics by deploying machine learning models on edge devices, allowing for real-time analysis of production data without relying solely on centralized processing.

Perform Production Reporting: Production reporting is streamlined through data science tools. Automated reporting systems powered by machine learning algorithms can generate comprehensive and accurate production reports, offering insights into key performance indicators and facilitating data-driven decision-making.

In summary, the Production Analytics function, empowered by data science, plays a crucial role in optimizing manufacturing processes and fostering business agility. From optimizing order lists and monitoring operations to achieving business agility goals such as improving behavioral and situational awareness, enabling inclusive and augmented decision-making, and creating dynamic processes and resources, data science enhances the overall efficiency, adaptability, and responsiveness of the production analytics function within the broader scope of supply chain collaboration and material management (Braun et al., 2020; Cattaneo et al., 2018; Fang et al., 2020; Flath & Stein, 2018; Gao et al., 2020; Klaeger et al., 2021; Lade et al., 2017; Shao et al., 2014).

4.4.3.5 Production Monitoring and supervision

The function of Production Monitoring and Supervision plays a pivotal role in ensuring the efficiency and effectiveness of manufacturing operations. This section delves into the key activities performed by this function as shown in *Figure 258*, encompassing the monitoring of machines and lines, analysis of Overall Equipment Efficiency (OEE), KPI calculation and reporting, tracking energy and resource consumption, and machine data acquisition. Additionally, I explore how data science can be harnessed to achieve business agility goals within this function.

Monitor Machines and Lines: Machine and line monitoring involves real-time tracking of production equipment and assembly lines. Data science enables the integration of sensors and IoT devices to collect and analyze machine-generated data, providing insights into performance, downtime, and overall operational efficiency.

Analyze OEE and Trigger Continuous Improvement Process: Overall Equipment Efficiency (OEE) analysis is vital for identifying inefficiencies in production processes.

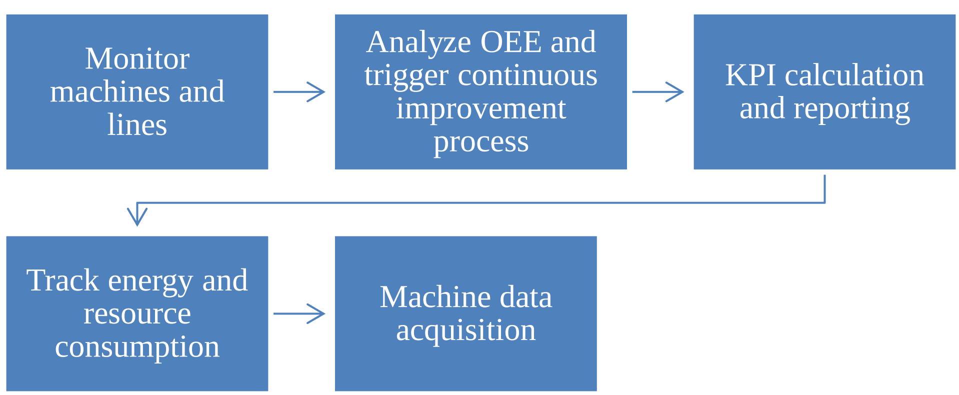

Figure 259 Typical Process Flow of Production Monitoring and supervision. Source: Author

Data science facilitates continuous improvement by applying predictive analytics to OEE data. This allows for the proactive identification of potential issues and the initiation of improvement processes before they impact production.

KPI Calculation and Reporting: Key Performance Indicators (KPIs) are crucial metrics for assessing production performance. Data science streamlines KPI calculation and reporting by automating the collection and analysis of relevant data. This ensures accurate and timely reporting, enabling data-driven decision-making.

Track Energy and Resource Consumption: Monitoring and optimizing energy and resource consumption are essential for sustainable and cost-effective manufacturing. Data science helps in tracking and analyzing energy and resource usage patterns, facilitating the identification of areas for optimization and efficiency improvements.

Machine Data Acquisition: Data acquisition from machines involves gathering detailed information on machine operations. Data science enables comprehensive machine data acquisition by processing and interpreting vast datasets, extracting actionable insights, and providing a holistic view of machine performance.

In summary, the Production Monitoring and Supervision function, empowered by data science, plays a crucial role in ensuring efficient and agile manufacturing operations. By leveraging AI tools for behavioral and situational awareness, inclusive and augmented decision-making, as well as dynamic process and resource management, businesses can achieve heightened agility in their production processes (Abele et al., 2015; Cachapa et al., 2010; Halme et al., 2019; Kulcsár et al., 2016; Subramaniam et al., 2009).

4.4.3.6 Shopfloor Quality inspection execution

The function of "Shopfloor Quality Inspection Execution" is a critical component within the broader operational framework, focusing on maintaining quality standards through a series of activities as shown in *Figure 260*. This section delves into the intricacies of these activities and explores how data science can be applied to enhance each step. Additionally, it discusses how leveraging data science can contribute to achieving specific business agility goals within this function.

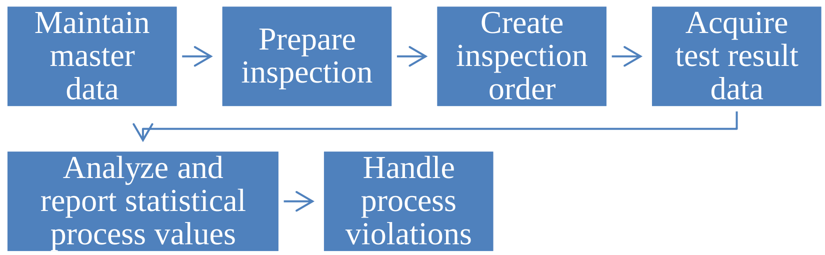

Figure 261 Typical Process Flow of Shopfloor Quality inspection execution. Source: Author

Maintain Master Data: This involves the upkeep of master data related to products, materials, and inspection criteria. Data science algorithms can automate the maintenance of master data by analyzing historical patterns, identifying inconsistencies, and suggesting updates, ensuring accuracy and relevance.

Prepare Inspection: Preparation for inspection involves defining the inspection plan, selecting appropriate criteria, and ensuring the availability of necessary resources. Machine learning models can optimize inspection preparation by predicting the most effective inspection criteria based on historical data, ensuring thorough and targeted quality assessments.

Create Inspection Order: This activity entails generating orders to conduct inspections based on the predefined criteria. Automated systems driven by data science can optimize the creation of inspection orders by considering factors such as production schedules, resource availability, and historical inspection outcomes.

Acquire Test Result Data: Involves the collection of test result data during inspections. Automated data collection systems enhanced by data science can streamline the acquisition of test result data, reducing manual efforts and minimizing the risk of errors.

Analyze and Report Statistical Process Values: This involves analyzing collected data to derive statistical process values and generating reports. Advanced analytics and machine learning algorithms can analyze large datasets in real-time, providing insights into statistical process values and automating the generation of comprehensive reports.

Handle Process Violations: In case of deviations from quality standards, this activity involves initiating corrective actions. Predictive modeling can anticipate potential process violations based on historical data, enabling proactive measures, and contributing to continuous improvement.

In summary, the integration of data science into Shopfloor Quality Inspection Execution activities offers a data-driven approach to maintaining quality standards. Leveraging data science not only enhances the efficiency of inspection-related processes but also contributes to achieving crucial business agility goals, ensuring adaptability, responsiveness, and continuous improvement within the operational framework (Cappiello et al., 2017; Hiruta et al., 2019; Oh et al., 2001; Rodic & Baranovic, 2009; Sajid et al., 2021; Shull et al., 2012; Wang et al., 2023; West et al., 2021).

4.4.3.7 In operation machine performance management

The function responsible for "In Operation Machine Performance Management" is pivotal in maintaining and optimizing the performance of machinery during active operations. This multifaceted role involves activities as shown in *Figure 262* ranging from simulation execution to statistical process analysis and operator training. The integration of data science into these activities enhances efficiency, accuracy, and adaptability.

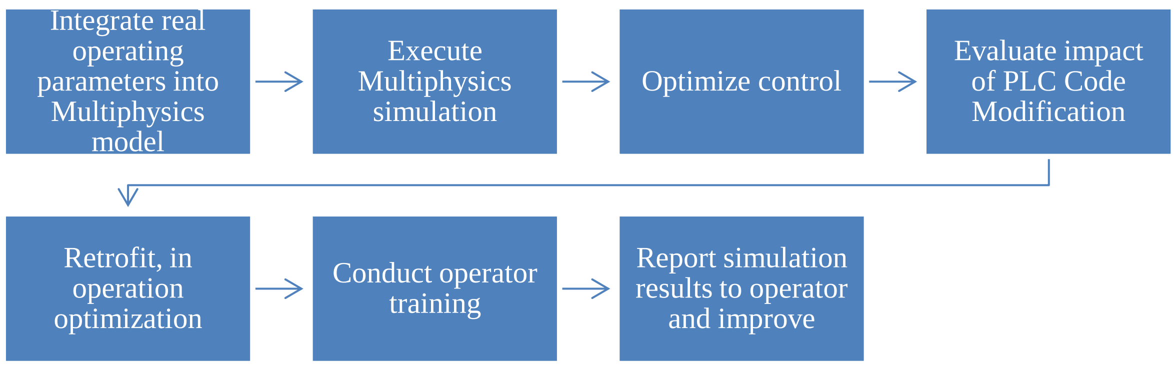

Figure 263 Typical Process Flow of In operation machine performance management. Source: Author

Integrate real operating parameters into Multiphysics model: Data science plays a crucial role in this activity by assimilating real-time operating parameters into Multiphysics models. Advanced algorithms ensure accurate integration, enabling simulations that closely mirror real-world conditions.

Execute Multiphysics simulation: Data science contributes to the execution of Multiphysics simulations by optimizing computational processes, reducing simulation time, and enhancing the accuracy of results through iterative learning.

Optimize control: Machine learning algorithms can analyze control parameters, identify patterns, and recommend optimizations to enhance overall control efficiency. This leads to adaptive control systems that respond dynamically to changing operational conditions.

Evaluate impact of PLC Code Modification: Data science aids in assessing the impact of Programmable Logic Controller (PLC) code modifications. Through simulation and analysis, potential consequences can be evaluated before implementation, minimizing operational disruptions.

Retrofit, in operation optimization: Data-driven insights enable effective retrofitting and in-operation optimization by analyzing historical data, identifying areas for improvement, and recommending modifications to enhance machine performance.

Conduct operator training: Data science supports operator training by simulating real-world scenarios, providing personalized training modules, and assessing operator performance, contributing to skill enhancement and operational efficiency.

Report simulation results to operator and improve: Advanced reporting tools powered by data science deliver simulation results to operators in a comprehensible format. Continuous improvement is achieved through iterative analysis, learning from simulation outcomes, and implementing enhancements.

Maintain master data: Data science automates master data maintenance by identifying inconsistencies, recommending updates, and ensuring data accuracy, contributing to a reliable foundation for performance management.

Prepare inspection: Predictive analytics models can forecast optimal inspection schedules based on historical data, equipment performance, and operational patterns, ensuring proactive maintenance and minimizing downtime.

Create inspection order: Automation of inspection order creation is facilitated by data science, ensuring that orders align with predictive maintenance schedules and operational priorities.

Acquire test result data: Data science streamlines the acquisition of test result data by automating data collection processes, reducing manual intervention, and ensuring the accuracy of results.

Analyze and report statistical process values: Statistical process analysis is enhanced through data science by automating value analysis, identifying trends, and generating actionable reports for informed decision-making.

Handle process violations: Machine learning algorithms can detect and handle process violations in real-time, providing instant alerts and recommendations for corrective actions, ensuring operational compliance and efficiency.

In conclusion, the function of "In Operation Machine Performance Management" integrates data science to optimize machine performance during active operations. From simulation execution and process optimization to training and maintenance, data science enhances efficiency, accuracy, and adaptability. Additionally, employing data science for business agility goals ensures behavioral awareness, situational awareness, inclusive decision-making, augmented decision-making, and dynamic processes and resources for fast execution, contributing to an agile and responsive operational framework (Ganapathi, 2009; Kibira et al., 2015; Pospisil et al., 2016; Sajid et al., 2021; Väyrynen et al., 2015; Walker, 2020).

4.4.3.8 Virtual workspace and work methods

The function responsible for "Virtual Workspace and Work Methods" encompasses a range of activities leveraging cutting-edge technologies to create collaborative and efficient work environments. These activities as shown in *Figure 264* include the utilization of augmented and virtual reality, hybrid or mixed reality, virtual desktops, digital dashboards, and wearables.

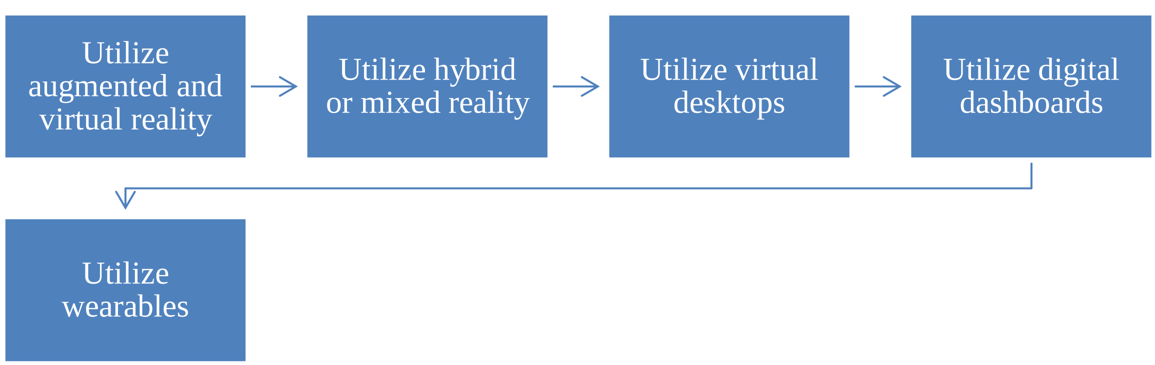

Figure 265 Typical Process Flow of Virtual workspace and work methods.
Source: Author

Utilizing augmented and virtual reality involves the integration of computer-generated information with the user's real-world environment, enhancing perception and interaction. Data science plays a role in optimizing user experiences by analyzing usage patterns, preferences, and performance metrics, contributing to the continuous improvement of virtual reality applications.

Hybrid or mixed reality involves combining aspects of both physical and virtual environments. Data science contributes by analyzing real-world and virtual interactions, providing insights into user behavior and preferences. This analysis aids in refining mixed reality experiences and tailoring them to user needs.

Virtual desktops offer a virtualized environment for users to access applications and data remotely. Data science is applied to optimize virtual desktop performance, analyzing usage patterns to allocate resources efficiently, ensuring a seamless and responsive user experience.

Digital dashboards provide visual representations of key data and metrics. Data science enhances these dashboards by analyzing diverse data sources, identifying patterns, and offering predictive insights. This aids in creating more informative and actionable dashboards that support decision-making.

Wearables, such as smart glasses or fitness trackers, bring digital information into the physical workspace. Data science contributes by analyzing wearable data, extracting meaningful insights, and providing personalized recommendations. This enhances the effectiveness of wearables in supporting user tasks and activities.

In summary, the "Virtual Workspace and Work Methods" function, with a focus on virtual and augmented technologies, can leverage data science for enhanced user experiences and improved business agility. From optimizing virtual reality applications to fostering inclusive decision-making and dynamic process automation, data science plays a pivotal role in shaping a responsive and efficient work environment. The integration of AI-driven analytics ensures organizations stay ahead in adapting to evolving trends and challenges, ultimately promoting business agility (Cavallo et al., 2019; Keahey et al., 2007; Kwon et al., 2018; Sailer et al., 2015; Weber et al., 2015).

4.4.3.9 Mitigation Strategies for Challenges in Adoption of Data Science

The integration of data science in the Manufacturing Execution or Operations department revolutionizes industrial production by optimizing processes and enhancing decision-making. From defect tracking to virtual workspaces, data science empowers organizations to monitor, analyze, and improve various aspects of production. This section explores how data science transforms typical functions within the Industrial Production Monitoring and Analytics domain. Table 38 summarizes the different data science use cases in this domain, associated challenges and risk along with the proposed mitigation strategies that can be taken by organizations.

Table 38 Data Science Use Cases for the various process in Shop Floor Logistics - Intra-Plant Logistics Management. Source: Author

Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
Defect Tracking and Non-Conformance Management	Predictive maintenance, anomaly detection, natural language processing	Lack of skilled workforce, Data quality and availability, Integration with existing systems	Increased production downtime, compromised product quality, delayed issue resolution	Provide comprehensive training programs, implement data validation protocols, streamline system integration processes

Table 38 Data Science Use Cases for the various process in Shop Floor Logistics - Intra-Plant Logistics Management. Source: Author

Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
Integrated Energy Management	Predictive analytics, anomaly detection, optimization algorithms	Lack of skilled workforce, Data quality and availability, Privacy, and security concerns	Energy inefficiencies, inaccurate forecasts, data breaches	Offer training on energy management techniques, establish data validation procedures, enhance cybersecurity measures
Equipment Analytics	Predictive maintenance, anomaly detection, machine learning models	Lack of skilled workforce, Integration with existing systems, Lack of standardization	Unplanned downtime, suboptimal maintenance schedules, data silos	Conduct training on equipment analytics tools, integrate systems with standardized protocols, establish data governance policies
Production Analytics	Predictive analytics, optimization algorithms, edge analytics	Data quality and availability, Integration with existing systems, Alignment with business objectives	Inaccurate forecasts, suboptimal production schedules, misaligned strategies	Implement data quality improvement initiatives, streamline integration processes, ensure alignment with strategic goals

Table 38 Data Science Use Cases for the various process in Shop Floor Logistics - Intra-Plant Logistics Management. Source: Author

Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
Production Monitoring and Supervision	Real-time monitoring, anomaly detection, predictive analytics	Lack of skilled workforce, Data quality and availability, Scalability	Inaccurate insights, delayed decision-making, overwhelmed workforce	Provide training on monitoring tools, enhance data quality assurance processes, invest in scalable infrastructure
Shopfloor Quality Inspection Execution	Statistical process control, anomaly detection, machine vision	Lack of skilled workforce, Data quality and availability, Privacy, and security concerns	Inaccurate inspections, compromised data integrity, unauthorized access	Offer specialized training programs, implement data validation measures, enhance access control mechanisms
In Operation Machine Performance Management	Multiphysics simulation, optimization algorithms, predictive analytics	Integration with existing systems, Scalability, Lack of standardization	Integration complexities, scalability issues, inconsistent processes	Standardize integration processes, invest in scalable infrastructure, establish data governance frameworks

Table 38 Data Science Use Cases for the various process in Shop Floor Logistics - Intra-Plant Logistics Management. Source: Author				
Process	**Data Science Use Cases**	**Challenges**	**Risk**	**Mitigation Strategies**
Virtual Workspace and Work Methods	Augmented reality, virtual reality, digital dashboards	Lack of skilled workforce, Integration with existing systems, Alignment with business objectives	Training gaps, system compatibility issues, misaligned strategies	Provide comprehensive training on virtual tools, streamline integration processes, ensure alignment with business goals

In conclusion, as destained out in Table 38, leveraging data science in Industrial Production Monitoring and Analytics enhances agility and efficiency in manufacturing operations. By addressing challenges such as data quality, integration complexities, and workforce skills gaps, organizations can unlock the full potential of data-driven insights. Embracing AI-driven solutions fosters improved situational awareness, enables augmented decision-making, and facilitates the creation of dynamic processes and resources, ultimately driving competitive advantage in the ever-evolving manufacturing landscape.

4.4.4 Mitigation Strategies for Challenges in Adoption of Data Science in Cross Domain Integrations

In the realm of Industrial Production Monitoring and Analytics within a Manufacturing Execution function, the utilization of data science in cross domain integration function and its sub activities as shown in *Figure 266***,** plays a pivotal role in enhancing operational efficiency and decision-making across various business processes. This section discusses different data science use cases in this domain, associated challenges and risk along with the proposed mitigation strategies that can be taken by organizations.

Figure 267 Typical Sub Functions of Cross Domain Integrations. Source: Author

Integration of data science within the sub-functions of Cross Domain Integrations not only optimizes individual processes but also fosters a synergistic manufacturing ecosystem. From predictive maintenance and quality control to adaptive scheduling and demand forecasting, data science catalyzes a paradigm shift in how manufacturing execution functions operate. The transformative impact of data science is evident in its ability to elevate efficiency, reduce costs, and enhance the overall agility of industrial production monitoring and analytics (Fisher et al., 2020; Hufnagel & Vogel-Heuser, 2015; Kiourtis et al., 2016; Kirmse et al., 2019; Lechevalier et al., 2016; Mavrogiorgou et al., 2022; Modoni et al., 2017; Obraczka, 2022; Sartipi & Dehmoobad, 2008; Yang, 2016).

4.4.4.1 Closed Loop Manufacturing Integration

Within the Manufacturing Execution Organization, the function of Closed Loop Manufacturing Integration plays a pivotal role in ensuring seamless coordination between manufacturing planning and execution. This section explores the key activities as shown in *Figure 268* within this function and delves into how data science can enhance each process. Subsequently, it discusses how data science can contribute to achieving specific business agility goals, fostering a more responsive and adaptive manufacturing environment.

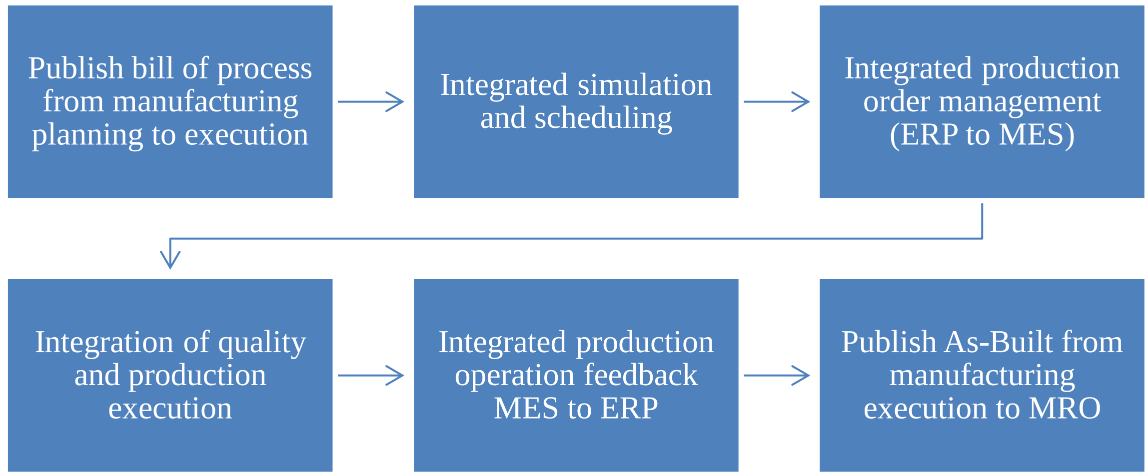

Figure 269 Typical Process Flow of Closed Loop Manufacturing Integration. Source: Author

Publish Bill of Process from Manufacturing Planning to Execution: Data Science Application: Predictive analytics models can analyze historical process data, optimizing the publishing of bills of process. Machine learning algorithms can predict potential bottlenecks and suggest improvements, ensuring a more efficient transition from planning to execution.

Integrated Simulation and Scheduling: Data Science Application: Simulation models powered by data science can simulate various production scenarios, considering historical data and real-time conditions. Machine learning algorithms can optimize scheduling by predicting production outcomes and adapting schedules dynamically based on emerging trends.

Integrated Production Order Management (ERP to MES): Data Science Application: Data science contributes by automating order management processes through predictive modeling. Machine learning algorithms can optimize the assignment of production orders by considering real-time resource availability, historical order data, and dynamic production conditions.

Integration of Quality and Production Execution: Data Science Application: Quality integration benefits from data-driven predictive models that analyze historical quality data.

Machine learning algorithms can predict potential quality issues, optimizing the integration of quality processes with production execution for proactive quality management.

Integrated Production Operation Feedback MES to ERP: Data Science Application: Data science enhances feedback processes by analyzing real-time production data. Machine learning models can provide insights into operational performance, enabling timely feedback to ERP systems for informed decision-making and performance optimization.

Publish As-Built from Manufacturing Execution to MRO: Data Science Application: The publication of as-built data can be optimized through data science-driven analytics. Predictive models can assess the relevance of as-built information, ensuring accurate and timely publication for Maintenance, Repair, and Overhaul (MRO) processes.

The Closed Loop Quality Integration within the Manufacturing Execution Organization involves critical activities such as publishing bills of process, simulation and scheduling, production order management, quality integration, operation feedback, and publishing as-built data. Data science applications in each of these activities optimize processes, enhance decision-making, and contribute to the overall efficiency of manufacturing operations. Moreover, by achieving specific business agility goals, data science ensures that manufacturing processes are not only responsive but also adaptive to the dynamic demands of the industrial landscape (Adam & Gangopadhyay, 1993; Barton et al., 2018; Hufnagel & Vogel-Heuser, 2015; Kibira et al., 2015; Lynn et al., 2015).

4.4.4.2 Closed Loop Quality Integration

Within the Manufacturing Execution Organization, the "Closed Loop Quality Integration" function is integral for ensuring a seamless integration of quality planning and execution processes. This section explores the activities as shown in *Figure 270* performed by this function, specifically the publication of quality planning definitions to quality execution and the consolidation of quality execution and inspection results. Additionally, it delves into how data science can enhance these activities. Furthermore, the discussion extends to improving business agility goals through data science integration.

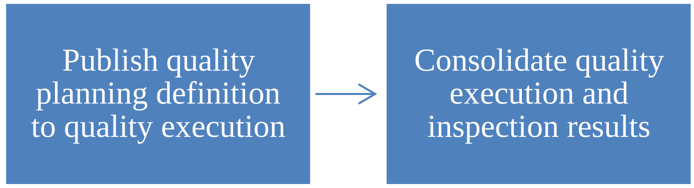

Figure 271 Typical Process Flow of Closed Loop Quality Integration. Source: Author

Publish Quality Planning Definition to Quality Execution: This activity involves disseminating the defined quality planning parameters and standards to the execution phase. Data science can enhance this process by automating the translation of planning definitions into actionable insights. Predictive analytics models can forecast potential challenges in execution, allowing proactive measures to be taken.

Consolidate Quality Execution and Inspection Results: This activity focuses on gathering and consolidating data from quality execution and inspection processes. Data science plays a crucial role in automating the consolidation of large datasets. Machine learning algorithms can analyze results, identify patterns, and provide actionable insights for decision-makers to improve overall quality.

In summary, the Closed Loop Quality Integration function in the Manufacturing Execution Organization involves critical activities such as publishing quality planning definitions and consolidating execution and inspection results. Integration of data science enhances these activities by automating processes and providing actionable insights. Furthermore, by leveraging data science for business agility goals, the organization can achieve improved behavioral awareness, situational awareness, inclusive decision-making, augmented decision-making, dynamic processes, and dynamic resource allocation (Abdel-Moneim et al., 2015; Colledani & Yemane, 2010; Krogstie, 2013; Saif & Yusof, 2019; West et al., 2021).

4.4.4.3 Part Manufacturing Management integration

Within the Manufacturing Execution Organization, the function responsible for "Part Manufacturing Management Integration" plays a crucial role in coordinating and optimizing part manufacturing processes. This function encompasses activities as shown in *Figure 272* such as publishing part programs, triggering CNC machines, and consolidating machine results into an As-Built record.

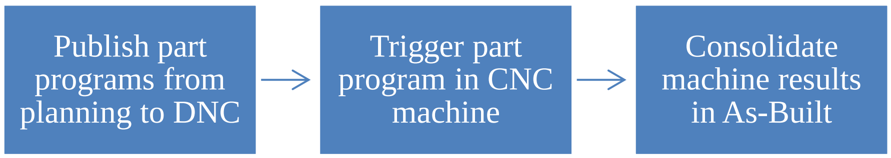

Figure 273 Typical Process Flow of Part Manufacturing Management integration. Source: Author

Publish Part Programs from Planning to DNC: This involves the seamless transition of part programs from the planning phase to the DNC (Distributed Numerical Control) system, ensuring that the machine instructions are readily available for CNC machines on the shop floor. Data science can optimize this process by predicting the most efficient scheduling and routing of part programs. Machine learning algorithms can analyze historical data, machine availability, and production priorities to optimize the publication process.

Trigger Part Program in CNC Machine: This activity involves initiating the part program on CNC machines, ensuring the accurate execution of manufacturing instructions and the production of high-quality parts. Predictive maintenance models can be employed to anticipate potential machine failures, minimizing downtime. Additionally, real-time monitoring using IoT sensors can provide data for continuous improvement, ensuring optimal machine performance.

Consolidate Machine Results in As-Built: After part manufacturing, the As-Built record is created, consolidating all relevant information about the produced parts, including any deviations from the original plan. Data analytics can be applied to the As-Built records to identify patterns and insights regarding production variations. This data-driven approach supports continuous improvement by highlighting areas for process optimization and quality enhancement.

The "Part Manufacturing Management Integration" function in the Manufacturing Execution Organization, with its focus on publishing part programs, triggering CNC machines, and consolidating machine results, is empowered by data science. The integration of AI tools improves behavioral and situational awareness, fosters inclusive and augmented decision-making, and creates dynamic processes and resources for fast execution, thereby enhancing business agility in the manufacturing domain (Hufnagel & Vogel-Heuser, 2015; Lechevalier et al., 2016; Qiao & McLean, 2004; Urbina et al., 2018; Vafeiadis et al., 2019; Zhang et al., 2019).

4.4.4.4 Supply Chain Synchronization integration

The Manufacturing Execution Organization oversees the critical function of Supply Chain Synchronization Integration, which involves harmonizing various elements of the manufacturing process as shown in *Figure 274* to optimize efficiency. This section explores the activities of Integrated Routing Management, Integrated Part Master Data Management, and Integrated Bill of Material Management within this function.

Figure 275 Typical Process Flow of Supply Chain Synchronization integration. Source : Author

Additionally, it delves into how data science can enhance each activity. Subsequently, the discussion transitions to how utilizing data science can achieve business agility goals, including improving behavioral awareness, situational awareness, enabling inclusive and augmented decision-making, and creating dynamic processes and resources for fast execution.

Integrated Routing Management (ERP to MRP): This activity involves seamlessly managing the flow of manufacturing processes from Enterprise Resource Planning (ERP) to Material Requirements Planning (MRP). Data science can optimize routing decisions by analyzing historical production data, predicting bottlenecks, and recommending dynamic routing strategies based on real-time conditions.

Integrated Part Master Data Management (PLM to ERP): Managing part master data from Product Lifecycle Management (PLM) to ERP systems requires precision. Data science can enhance this process by automating data validation, ensuring consistency across systems, and leveraging machine learning models to predict part data changes, facilitating proactive management.

Integrated Bill of Material Management (PLM to ERP): Harmonizing the Bill of Materials (BOM) between PLM and ERP systems is crucial. Data science aids in this activity by utilizing algorithms to reconcile BOM variations, conducting predictive analysis to anticipate changes, and optimizing BOM structures based on historical usage and performance data.

In conclusion, Supply Chain Synchronization Integration in the Manufacturing Execution Organization involves activities such as Integrated Routing Management, Integrated Part Master Data Management, and Integrated Bill of Material Management. Leveraging data science enhances these activities, optimizing routing decisions, ensuring data consistency, and reconciling BOM variations. Moreover, utilizing data science for business agility goals improves behavioral awareness, situational awareness, decision-making inclusivity, and augmentation, as well as the creation of dynamic processes and resources for fast execution. This data-driven approach ensures the organization's adaptability, responsiveness, and efficiency within the manufacturing supply chain (Górtowski, 2019; Pereira & Frazzon, 2021; Pires et al., 2017; Robak et al., 2013; Sakib, 2021).

4.4.4.5 Mitigation Strategies for Challenges in Adoption of Data Science

In today's rapidly evolving manufacturing landscape, the integration of data science into cross-domain operations has become imperative for maintaining competitiveness and agility. This table presents a comprehensive overview of how data science can be applied across various functions within a Manufacturing Execution or Operations department, specifically focusing on Cross Domain Integrations. By leveraging advanced analytics, machine learning, and predictive modeling, organizations can optimize processes, enhance decision-making capabilities, and achieve greater business agility. However, the adoption of data science in manufacturing is not without its challenges, including skill shortages, data quality issues, and integration complexities. Understanding these challenges and implementing effective mitigation strategies is crucial for successful implementation and realization of the benefits offered by data science.

Closed Loop Quality Integration ensures seamless flow of quality planning from definition to execution, consolidating inspection results for comprehensive quality management. By integrating quality processes, organizations can streamline quality assurance, enhance defect tracking, and improve product consistency. Table 39 summarizes the different data science use cases in this domain, associated challenges and risk along with the proposed mitigation strategies that can be taken by organizations.

Table 39 Data Science Use Cases for the various process in Cross Domain Integrations - Closed Loop Quality Integration. Source: Author

Data Science Use Cases	**Challenges**	**Risk**	**Mitigation Strategies**
Predictive maintenance to optimize equipment uptime	Lack of skilled workforce, Data quality and availability, Integration with existing systems	Delayed production, Reduced operational efficiency, Increased downtime	Provide training programs to upskill existing workforce, implement data quality checks and data cleansing processes, Use standardized integration protocols and APIs
Machine learning for demand forecasting and production scheduling	Lack of standardization, Integration with existing systems, Alignment with business objectives	Suboptimal production schedules, Poor resource allocation, Missed delivery deadlines	Establish data governance framework, ensure interoperability between systems, Align data science initiatives with organizational objectives
Anomaly detection for quality control and defect tracking	Lack of skilled workforce, Data quality and availability, Privacy, and security concerns	Increased defect rates, Quality issues in final products, Regulatory non-compliance	Invest in training programs for data science skills, implement data quality checks and encryption protocols, Comply with data privacy regulations

Table 39 Data Science Use Cases for the various process in Cross Domain Integrations - Closed Loop Quality Integration. Source: Author			
Data Science Use Cases	**Challenges**	**Risk**	**Mitigation Strategies**
Natural language processing for analyzing and extracting insights from quality reports	Data quality and availability, Integration with existing systems, Lack of standardization	Inaccurate analysis, missed insights, Decision-making based on incomplete information	Implement data quality checks and data cleansing processes, standardize data formats and reporting procedures, Provide training on data interpretation and analysis techniques
Machine learning for predictive quality modeling and defect prediction	Lack of skilled workforce, Data quality and availability, Integration with existing systems	Increased defect rates, Poor quality control, Missed opportunities for process improvement	Invest in training programs for data science skills, implement data quality checks and data cleansing processes, Ensure interoperability between quality management systems

This integration facilitates real-time monitoring and feedback loops, enabling prompt corrective actions and continuous improvement initiatives. Ultimately, Closed Loop Quality Integration contributes to enhancing product quality, customer satisfaction, and overall operational efficiency in manufacturing environments.

Part Manufacturing Management integration involves seamlessly linking part program management from planning to execution. This process ensures the efficient transmission of part programs from the planning stage to the Direct Numerical Control (DNC) machines. Table 40 summarizes the different data science use cases in this domain, associated challenges and risk along with the proposed mitigation strategies that can be taken by organizations.

Table 40 Data Science Use Cases for the various process in Cross Domain Integrations - Part Manufacturing Management Integration. Source: Author

Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Machine learning for optimizing part manufacturing processes and reducing cycle times	Improve Situational Awareness, enable augmented decision making	Lack of standardization, Integration with existing systems, Alignment with business objectives	Suboptimal manufacturing processes, Increased lead times, Missed production targets	Establish data governance framework, ensure interoperability between systems, Align data science initiatives with organizational objectives
Anomaly detection for detecting deviations in part manufacturing processes	Improve Situational Awareness, enable augmented decision making	Data quality and availability, Integration with existing systems, Lack of standardization	Increased defect rates, Poor product quality, Missed opportunities for process improvement	Implement data quality checks and data cleansing processes, standardize data formats and reporting procedures, Ensure interoperability between manufacturing and quality management systems

By triggering the part programs in CNC machines and consolidating machine results in the As-Built database, organizations can streamline part manufacturing processes, reduce errors, and improve overall production efficiency and accuracy.

Supply Chain Synchronization integration involves aligning production planning and execution with supply chain processes to optimize efficiency and responsiveness. It facilitates seamless communication between enterprise resource planning (ERP) and material requirements planning (MRP) systems, streamlining routing management and part master data management. By integrating bill of material (BOM) management, it ensures accurate and synchronized information flow across the supply chain, enabling organizations to adapt quickly to changing demand and market conditions while minimizing disruptions. Table 41 summarizes the different data science use cases in this domain, associated challenges and risk along with the proposed mitigation strategies that can be taken by organizations.

Table 41 Data Science Use Cases for the various process in Cross Domain Integrations - Supply Chain Synchronization integration. Source: Author

Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Machine learning for supply chain risk management and supplier performance prediction	Improve Situational Awareness, enable augmented decision making	Privacy and security concerns, Scalability, Lack of standardization	Supply chain disruptions, Poor supplier performance, Increased procurement costs	Implement encryption protocols and access controls, Design scalable machine learning models, Establish data governance framework

Table 41 Data Science Use Cases for the various process in Cross Domain Integrations - Supply Chain Synchronization integration. Source: Author				
Data Science Use Cases	**Business Agility Goals**	**Challenges**	**Risk**	**Mitigation Strategies**
Natural language processing for analyzing and extracting insights from supply chain data	Improve Behavioral Awareness, enable augmented decision making	Data quality and availability, Integration with existing systems, Lack of standardization	Inaccurate analysis, missed insights, Decision-making based on incomplete information	Implement data quality checks and data cleansing processes, standardize data formats and reporting procedures, Provide training on data interpretation and analysis techniques

In conclusion, the integration of data science into cross-domain operations in manufacturing offers immense potential for driving operational excellence and business agility. By harnessing advanced analytics and machine learning techniques, organizations can optimize processes, improve decision-making, and adapt to dynamic market conditions more effectively. However, achieving these benefits requires addressing various challenges such as skill shortages, data quality issues, and integration complexities. By implementing robust mitigation strategies and fostering a data-driven culture, manufacturing enterprises can overcome these challenges and unlock the full potential of data science to drive innovation and competitive advantage.

5. SUMMARY, IMPLICATIONS, AND RECOMMENDATIONS

5.1 Summary

The thesis presents an exhaustive examination of the challenges encountered in adopting data science within the context of Industry 4.0, focusing on its application in product design, supply chain management, manufacturing planning, engineering, execution, and cross-domain integrations. Each section meticulously delineates the specific hurdles faced in these domains and proposes a comprehensive set of mitigation strategies to address them effectively. From program management to shop floor logistics, the thesis offers a granular understanding of the obstacles impeding the seamless integration of data science into industrial processes and provides actionable recommendations to overcome them.

The research conducted involves a comprehensive analysis of literature to explore data science applications, challenges, and mitigation strategies across various domains within the manufacturing industry. In the realm of Product Design and Development, findings from 316 research articles shed light on a multitude of data science use cases and challenges, spanning functions such as PLM collaboration, supply chain management, and software design. Similarly, the examination of 121 articles focusing on Manufacturing Planning reveals insights into process optimization, resource allocation, and simulation techniques, with a particular focus on Manufacturing Process Planning and Specialized Manufacturing Process Planning. Additionally, the analysis of 122 articles centered on Manufacturing Engineering uncovers data science applications in systems design, automation, and asset management, alongside associated challenges, and mitigation strategies. Moreover, insights gleaned from 128 articles on Manufacturing Execution elucidate data-driven approaches to production monitoring, logistics management, and industrial analytics, aiming to enhance operational excellence in manufacturing environments. Overall, the synthesis of these findings aims to inform actionable recommendations for leveraging data science to drive efficiency, agility, and innovation in the Industry 4.0/5.0 landscape.

Furthermore, the research findings highlight the rich diversity of data science applications and challenges encountered across different functional domains within the manufacturing sector. From PLM collaboration to Manufacturing Execution, each area presents unique opportunities and obstacles in harnessing the power of data science for operational enhancement and innovation. The analysis underscores the critical importance of addressing challenges such as data quality issues, integration complexities, workforce skills gaps, and privacy concerns to unlock the full potential of data science initiatives. Mitigation strategies proposed in the literature offer valuable insights into how organizations can navigate these challenges, ranging from investment in training programs and data governance frameworks to the adoption of scalable cloud platforms and robust encryption methods. By synthesizing insights gleaned from the literature survey, this research endeavor aims to provide practical recommendations for manufacturing organizations seeking to leverage data science to optimize processes, enhance resource utilization, and drive continuous improvement in the Industry 4.0/5.0 paradigm. Through targeted interventions and strategic investments in data-driven technologies and capabilities, organizations can position themselves for sustained success and competitiveness in an increasingly digital and interconnected manufacturing landscape.

In the Product Design & Development function, data science adoption in Industry 4.0/5.0 projects faces challenges such as a lack of skilled workforce, data quality and availability issues, integration challenges with existing systems, privacy and security concerns, and scalability limitations.

Mitigation strategies include investing in training programs, implementing data cleansing and governance, adopting interoperable platforms and API integration, ensuring robust encryption and compliance with data protection laws, and using scalable cloud platforms and optimized data storage solutions.

Table 42 provides the top 5 answers to research questions in context of Product Design and Development function derived from 316 articles covering 6 major functions, 66 sub-functions, and around 300 activities of product design and development functions.

<table>
<tr><td colspan="3">Table 42 Answers to Research Questions in context of Product Design and Development. Source: Author</td></tr>
<tr><th>1. What are the typical challenges in the adoption of data science in Industry 4.0 / 5.0 projects?</th><th>2. How to mitigate these challenges when orchestrating digital transformation projects as part of Industry 4.0 / 5.0 projects with data science features?</th><th>3. How can these mitigation strategies be deployed for various functions in a typical organization?</th></tr>
<tr><td>Lack of skilled workforce</td><td colspan="2">Invest in training programs, collaborate with academic institutions to address the lack of skilled workforce.</td></tr>
<tr><td>Data quality and availability issues</td><td colspan="2">Implement data cleansing processes, invest in data governance to tackle data quality and availability issues.</td></tr>
<tr><td>Integration challenges with existing systems</td><td colspan="2">Adopt interoperable platforms, API integration to overcome integration challenges with existing systems.</td></tr>
<tr><td>Privacy and security concerns</td><td colspan="2">Implement robust encryption, compliance with data protection laws to address privacy and security concerns.</td></tr>
<tr><td>Scalability limitations</td><td colspan="2">Adopt scalable cloud platforms, optimize data storage solutions to mitigate scalability limitations.</td></tr>
</table>

In the Manufacturing Planning function, data science adoption in Industry 4.0/5.0 projects faces challenges including a lack of skilled workforce, data quality and availability issues, integration challenges with existing systems, privacy and security concerns, and inadequate expertise in predictive modeling and AI.

Mitigation strategies include providing specialized training in relevant fields, implementing rigorous data quality checks and data governance, collaborating with IT departments for seamless system integration, and ensuring robust encryption and compliance with data privacy regulations.

Table 43 provides the top 5 answers to research questions in context of manufacturing planning function derived from 121 articles covering 4 major functions, 32 sub-functions, and around 130 activities of manufacturing planning functions.

Table 43 Answers to Research Questions in context of Manufacturing Planning. Source: Author		
1. What are the typical challenges in the adoption of data science in Industry 4.0 / 5.0 projects?	2. How to mitigate these challenges when orchestrating digital transformation projects as part of Industry 4.0 / 5.0 projects with data science features?	3. How can these mitigation strategies be deployed for various functions in a typical organization?
Lack of skilled workforce	Provide specialized training in the relevant fields (predictive modeling, AI, etc.) to address the lack of skilled workforce.	
Data quality and availability issues	Implement rigorous data quality checks and invest in data governance to tackle data quality and availability issues.	
Integration challenges with existing systems	Collaborate with IT departments to seamlessly integrate new systems and technologies with existing ones, addressing integration challenges.	
Privacy and security concerns	Implement robust encryption, access controls, and ensure compliance with data privacy regulations to address privacy and security concerns.	
Inadequate expertise in respective fields (predictive modeling, AI, etc.)	Provide specialized training in the respective fields (predictive maintenance, optimization algorithms, etc.) to enhance expertise and address inadequacies.	

In the Manufacturing Engineering function, data science adoption in Industry 4.0/5.0 projects faces challenges including a lack of skilled workforce, data quality and availability issues, integration challenges with existing systems, privacy and security concerns, and inefficient processes.

Mitigation strategies include investing in training programs, implementing data quality checks and data governance, collaborating with IT departments for seamless integration, establishing standardized protocols to optimize processes, and ensuring robust data security measures and compliance with privacy regulations.

Table 44 provides the top 5 answers to research questions in context of manufacturing engineering derived from 122 articles covering 3 major functions, 29 sub-functions, and around 120+ activities of manufacturing engineering functions.

Table 44 Answers to Research Questions in context of Manufacturing Engineering. Source: Author

1. What are the typical challenges in the adoption of data science in Industry 4.0 / 5.0 projects?	2. How to mitigate these challenges when orchestrating digital transformation projects as part of Industry 4.0 / 5.0 projects with data science features?	3. How can these mitigation strategies be deployed for various functions in a typical organization?
Lack of skilled workforce	Invest in training programs to address the lack of skilled workforce.	
Data quality and availability issues	Implement data quality checks and invest in data governance to tackle data quality and availability issues.	
Integration challenges with existing systems	Collaborate with IT departments to seamlessly integrate new systems and technologies with existing ones, addressing integration challenges.	
Privacy and security concerns	Implement robust data security measures and ensure compliance with privacy regulations to address privacy and security concerns.	
Inefficient processes	Establish standardized protocols and optimize processes to mitigate inefficiencies.	

In the Manufacturing Execution function, data science adoption in Industry 4.0/5.0 projects faces challenges including a lack of skilled workforce, data quality and availability issues, integration challenges with existing systems, privacy and security concerns, and alignment with business objectives.

Mitigation strategies include investing in training programs, implementing data quality checks and data governance, collaborating with IT departments for seamless system integration, ensuring robust data security measures and compliance with privacy regulations, and aligning data science initiatives with business objectives through co-creation workshops.

Table 45 provides the top 5 answers to research questions in context of manufacturing execution derived from 128 articles covering 4 major functions, 26 sub-functions, and around 100+ activities of manufacturing execution functions.

Table 45 Answers to Research Questions in context of Manufacturing Execution. Source: Author

1. What are the typical challenges in the adoption of data science in Industry 4.0 / 5.0 projects?	2. How to mitigate these challenges when orchestrating digital transformation projects as part of Industry 4.0 / 5.0 projects with data science features?	3. How can these mitigation strategies be deployed for various functions in a typical organization?
Lack of skilled workforce	Invest in training programs to address the lack of skilled workforce.	
Data quality and availability issues	Implement data quality checks and invest in data governance to tackle data quality and availability issues.	
Integration challenges with existing systems	Collaborate with IT departments to seamlessly integrate new systems and technologies with existing ones, addressing integration challenges.	
Privacy and security concerns	Implement robust data security measures and ensure compliance with privacy regulations to address privacy and security concerns.	
Alignment with business objectives	Align data science initiatives with business objectives – Co Creation workshops along with business	

5.2 Implications

The implications of this research are profound and far-reaching for industries navigating the complexities of the Fourth Industrial Revolution. By meticulously identifying and addressing the challenges associated with data science adoption, the thesis equips organizations with the knowledge and strategies necessary to optimize their operations and stay competitive in an increasingly digitalized landscape. The proposed mitigation strategies offer tangible pathways for enhancing product design efficiency, streamlining supply chain collaboration, optimizing manufacturing processes, and achieving cross-domain integration. Ultimately, the implementation of these strategies holds the potential to unlock significant benefits, including improved product quality, enhanced operational agility, reduced costs, and accelerated time-to-market.

Furthermore, the thesis underscores the broader implications of successful data science adoption beyond individual organizations. By facilitating the efficient utilization of data-driven insights, these strategies can contribute to the advancement of Industry 4.0, fostering innovation, driving economic growth, and addressing societal challenges. Moreover, by promoting a culture of continuous improvement and technological innovation, the research lays the groundwork for sustainable development and resilience in the face of evolving industrial landscapes and market dynamics.

5.3 Research Limitations

While the research design outlined for this study is robust and comprehensive, there are several limitations that should be acknowledged. Firstly, the reliance on literature survey as the primary data collection method may introduce biases inherent in the selection and interpretation of research articles. Despite efforts to systematically sample articles from diverse sources and domains within the manufacturing sector, the scope of the study may inadvertently overlook niche or emerging topics that are underrepresented in the literature.

Secondly, the generalizability of findings may be constrained by the specific focus on data science use cases, challenges, and mitigation strategies within the selected domains of Product Design and Development, Manufacturing Planning, Manufacturing Engineering, and Manufacturing Execution. While these domains are foundational to manufacturing operations, variations in industry practices, technological landscapes, and organizational contexts may limit the transferability of findings to other sectors or domains.

Additionally, the depth of analysis within each functional domain may vary depending on the availability and depth of literature. While efforts have been made to include a diverse range of research articles, variations in the quality, rigor, and depth of analysis across different studies may impact the completeness and reliability of the findings.

Furthermore, the researcher's own biases and perspectives, particularly given their extensive experience in the manufacturing industry, may influence the interpretation and synthesis of research findings. While efforts will be made to mitigate bias through reflexivity and transparency in data analysis and interpretation, it is essential to acknowledge the potential for subjectivity in the research process.

Finally, while the study aims to propose mitigation strategies for challenges identified in the literature, the effectiveness and applicability of these strategies in real-world contexts may require further empirical validation and testing. Implementation of mitigation strategies may vary depending on organizational dynamics, resource constraints, and contextual factors, which may limit the immediate practical utility of the findings.

Despite these limitations, the research design outlined provides a valuable framework for exploring data science applications and challenges within the manufacturing domain, offering insights that can inform future research directions and practical interventions aimed at enhancing operational efficiency and innovation in Industry 4.0/5.0 environments.

5.4 Recommendations for Future Research

While the thesis provides a comprehensive framework for mitigating challenges in data science adoption, several avenues for future research warrant exploration. Firstly, longitudinal studies tracking the implementation of the proposed strategies in real-world industrial settings could offer valuable insights into their effectiveness and scalability over time. Additionally, comparative analyses across different industries and geographical regions could shed light on contextual variations and best practices in data science adoption. Furthermore, future research endeavors could delve deeper into the integration of emerging technologies such as quantum computing, generative AI, and blockchain with data science to unlock new opportunities for innovation and optimization. Moreover, interdisciplinary studies bridging the gap between data science, business management, and sustainability could provide holistic solutions to address environmental and social challenges while driving economic prosperity. With the outcomes from the research joined with methodologies like the digitalization piano as discussed by (Tomas & Nwaiwu, 2018) will help the organizations to come out with the required strategy for their digital transformation journey powered with data science. Below Table 42 is a sample digitalization piano framework created for supply chain. Research creating customized framework for each, and every function will further strengthen the fraternity to successfully embark on the digital transformation journey in manufacturing industry. Simillar research can also be extended to other support functions like finance, Human Resources, Sales, and Marketing functions.

<table>
<tr><td colspan="9">Table 46 Sample Digitalization Piano framework for Supply Chain
Source: Author</td></tr>
<tr><td colspan="4">Digitalization Piano - Supply Chain Data Science Projects</td><td colspan="5">Focus required.
(1 low, 5 High)</td></tr>
<tr><td rowspan="4">Digital Strategy</td><td rowspan="3"><u>Value Drivers</u></td><td>Cost</td><td>Inventory reduction</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td></tr>
<tr><td>Experience</td><td>Improve Supplier experience</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td></tr>
<tr><td>Platform</td><td>Build Collaboration platform</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td></tr>
<tr><td><u>Go Live Strategy</u></td><td>Design – Implement</td><td>Phased region wise implementation post successful pilot - Central control tower – integrated dashboard</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td></tr>
<tr><td rowspan="5">Digital Engagement</td><td rowspan="2"><u>Workforce</u></td><td rowspan="2">Employee digital Knowledge, skills, motivation</td><td>Multidisciplinary team</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td></tr>
<tr><td>Training on data science low code tools</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td></tr>
<tr><td rowspan="2"><u>Partners</u></td><td rowspan="2">Digital – Enabled partner ecosystem</td><td>Onboard partners / suppliers early</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td></tr>
<tr><td>Training on data science low code tools</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td></tr>
<tr><td><u>Organizational Structure</u></td><td></td><td>Short term strategic team to implement</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td></tr>
</table>

Table 46 Sample Digitalization Piano framework for Supply Chain
Source: Author

Digitalization Piano - Supply Chain Data Science Projects				Focus required. (1 low, 5 High)				
		How you are organized for digital	Proper blend of function & Digital team – data science resource on need basis	1	2	3	4	5
Digital Enablement	**Business Process**	Process digitalization	Automated with human in the loop	1	2	3	4	5
			Training on data science low code tools	1	2	3	4	5
	IT capability	IT Support for digital capabilities	Data lake and BI tools	1	2	3	4	5
			Model performance monitoring	1	2	3	4	5
	Culture	Organizational readiness for digital transformation	Digital collaborations tools	1	2	3	4	5
			Data driven reviews and follow up with partners, supplier and service providers	1	2	3	4	5

5.5 Conclusion

In conclusion, the comprehensive analysis of literature presented in this research underscores the transformative potential of data science in driving efficiency, innovation, and competitiveness across various functional domains within the manufacturing industry. Through an examination of over 500 research articles, spanning Product Design and Development, Manufacturing Planning, Manufacturing Engineering, and Manufacturing Execution, a rich tapestry of data science applications, challenges, and mitigation strategies has emerged. The findings reveal a diverse array of data science use cases, ranging from predictive analytics for resource allocation to machine learning for automated validation and predictive modeling for risk assessment. However, alongside these opportunities, the analysis also highlights a multitude of challenges, including data quality issues, integration complexities, workforce skills gaps, and privacy concerns, which must be navigated to realize the full potential of data science initiatives. Mitigation strategies proposed in the literature offer actionable insights for organizations seeking to overcome these challenges, emphasizing the importance of investment in training programs, data governance frameworks, interoperable platforms, and robust encryption methods. By aligning data science initiatives with business objectives, engaging stakeholders, and adopting a holistic approach to data management, manufacturing organizations can unlock new avenues for operational enhancement and innovation in the industry 4.0/5.0 landscape. Moving forward, it is imperative for organizations to embrace a culture of data-driven decision-making, continuous learning, and innovation to thrive in an increasingly digital and interconnected manufacturing environment. By leveraging the insights gleaned from this research, manufacturing leaders can chart a course towards sustainable growth, resilience, and competitiveness in the dynamic landscape of Industry 4.0/5.0.

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