IDENTIFYING THE FACTORS FOR THE ADOPTION OF EXPERT-BASED INTELLIGENT DECISION SUPPORT SYSTEMS BY SMALL AND MEDIUM ENTERPRISE ENTREPRENEURS IN INDIA

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ABSTRACT

IDENTIFYING THE FACTORS FOR THE ADOPTION OF EXPERT-BASED INTELLIGENT DECISION SUPPORT SYSTEMS BY SMALL AND MEDIUM ENTERPRISE ENTREPRENEURS IN INDIA

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The thesis aims to identify the factors for the adoption or Expert based of knowledge based decision support system, a model proposed by Tariq and Rafi in 2012 using Technology-Organisation-Environment framework by Small and Medium enterprises in India. The data was collected from 508 participants using simple random sampling from different parts of India. Structural equation modelling technique was used to derive results from the raw data. Hypothesis were developed on seven parameters and the analysis found that only two parameters to be significant in the study, namely the complexity factors and environment factors. It explains that those organisations that are willing to adopt the technology, they are weary of the negative impact the technology has brought. They feel that they will adopt this technology sooner or later or they will be forced to adopt this technology but the stakeholders should first get rid of the complexity factors and external factors to enable the technology's adoption.

Keywords

Factors of adoption, Intelligent decision support system, Tehnology-Organisation-Environment framework, Small and medium enterprises, India.

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CHAPTER I:
INTRODUCTION

1.1 Introduction

Tools have created an impression in Human history by changing how we work (Schmidt, 2020). Like the invention of the wheel that changed how we transport things, the introduction of record-keeping tools changed our ability to remember things (Schmidt, 2020). So we wonder what new tools can be made using Artificial Intelligence and machine learning (Schmidt, 2020). Artificial Intelligence for decision-making has been the most pursued topic in the history of Artificial Intelligence. (Wooldridge and Cowden, 2020).

Decision-making is "**the research of identifying and choosing alternatives based on the decision-makers weighs/values and preferences. First, all possible alternatives must be identified for making a decision. Then the best alternative is chosen regarding the goals, constraints, etc."** (Marugán and García Márquez, 2017).

The issue with professionals involved in organizational decision-making is that when they make a business decision, they frequently are motivated by the current situation and environment, intuition, knowledge of the problem, prior experience, emotions, wants, and partiality (Ostapov, 2022). However, highly data-driven firms are three times more likely to report significant advances in decision-making than those depending less on data, according to a PwC poll of more than 1,000 senior executives (Stobierski, 2021).

Gartner survey found that 65% **of the decisions made today are more complex compared to two years ago** (Prerna Singh, 2021)**.**

However, Artificial intelligence-powered decision-making has become a game-changer (Ostapov, 2022). When artificial intelligence is used to develop alternatives to a problem, such a system or application is called an Intelligent decision support system(Phillips-Wren, 2013). The artificial intelligence system processes and analyses data in real-time, make intelligent predictions and suggests the best possible decision based on the initially specified parameters (Ostapov, 2022).

So, there are two main differences between human and Artificial intelligence decision-making:

- First, artificial intelligence considers all available information, while humans consider limited data.

- Artificial intelligence is ultimately objective and neglects emotional factors (Ostapov, 2022).

Today, decision-making requires taking into account an increasing amount of data, information, and knowledge of different kinds and qualities in the company's various activities; competitiveness depends on their analysis and optimal exploitation(Hamrouni *et al.*, 2021)

Gartner conducted a survey in 2019, finding that 37 percent of companies and organizations use Artificial intelligence at work. Additionally, according to research by Gartner, 38% of healthcare doctors utilize computers to help diagnose diseases. These benefits, the possibility for financial gain, and the allure of ARTIFICIAL INTELLIGENCE-operated jobs are revolutionizing people's personal and professional lives worldwide. (Robert Pistone, 2022)

Therefore, the Intelligent decision support system is suggested in business decision-making. The following are some of the benefits it would bring to the organization.

1. Business Automation
2. Customer relationship management (CRM)
3. High ROI and better decisions (Prerna Singh, 2021)

1.2 Research Problem

Big data is one of the significant challenges in decision-making. However, a 2022 research found that 99.5% of acquired data was never used or examined (Tran, 2022). Thus, massive data expansion necessitates data analytics and business intelligence, which is when big data analytics becomes popular.

According to research, we generate 2.5 quintillion bytes of data daily (Madan, 2023). Today, businesses may access data from websites, business applications, social network pages, mobile devices, blogs, papers, archives, and more (Madan, 2023). Hence, Data alone will not improve one's business; there is a need to analyse and convert collected data into useful information.

Human beings have a lot of psychological flaws in decision-making. Some of them are

1. Heuristics help the brain make decisions and solve problems quickly. However, this can cause mistakes and misjudgments (Bharsakle, 2019).
2. Next is overconfidence, a cognitive bias that traps people in their inadequacy by overestimating their brains, talents, and judgment, leading to bad decisions (Bharsakle, 2019).
3. The hindsight bias occurs when people use prior knowledge to anticipate the result of a chance-dependent scenario (Bharsakle, 2019).
4. People sometimes perceive illusory correlations between unconnected occurrences. This assumes a one-time link between two variables (Bharsakle, 2019).

1.3 Purpose of research

AI powers decision-making in our data-driven environment. Companies and government organisations make wiser judgments using inadequate data to obtain competitive advantages (Jacobson, 2023). For example, many organisations utilise statistics to decide crime rate rises, gun safety policies, cancer detection, and weather forecasts (Jacobson, 2023).

Data-driven decision-making is the mantra of government, industry, and "tech-savvy" politicians(Jacobson, 2023). Data science is "follow the science." However, data alone cannot improve decision-making(Jacobson, 2023).

Extracting such information to improve decision-making is difficult (Jacobson, 2023).

AI models and algorithms drive decision-making. They systematically extract relevant data from data (Jacobson, 2023). These predictions, projections, and interpretations aid decision-making (Jacobson, 2023). AI finds new ways to enhance our lives, whether self-driving cars, medical detection, or online shopping (Jacobson, 2023).

Reasonably, these models and algorithms use complicated mathematics and statistics that few are qualified to understand (Jacobson, 2023). Nevertheless, these models and algorithms often yield astonishing outcomes, guiding judgments that are often superior to those made by humans (Jacobson, 2023). Therefore, data and algorithms that use it to make wiser judgments are valuable.

AI-driven business intelligence is the future. Data has powered business for decades (Barber, 2021). It helps business people make decisions and gives them customer insights(Barber, 2021). However, unfortunately, the brain cannot digest all the facts (Barber, 2021): Artificial Intelligence and business intelligence decision-making help.

Businesses love Artificial Intelligence because it learns (Barber, 2021). Data-driven decision-making improves learning (Barber, 2021). AI can learn data modelling (Barber, 2021). These models can accurately classify data (Barber, 2021). In real-time, models forecast, categorise, and suggest (Barber, 2021). This improves business choices.

1.4 Research Aim

To start the research, it is crucial to clearly define the research objectives and formulate research questions that address the factors influencing the adoption of AI-based decision making and IDSS. These objectives will guide the study and provide a clear focus. For example:

- What are the key technological factors affecting the adoption of AI-based decision making and IDSS?
- How do organisational factors influence the adoption of AI-based decision making and IDSS?
- What external factors impact the adoption of AI-based decision making and IDSS?

1.5 Research questions

The following are the research questions that would be used in the research.

1. Will Small and medium enterprises in India adopt Intelligent decision-support systems?
2. If yes, then what factors would enable them to adopt the technology
3. What challenges have to be met in order to aid adoption?

1.6 Significance of the Study

Research on the adoption of artificial intelligence (AI)-based decision making is of significant importance due to its potential to transform various industries and organisational processes. This research will highlight the key reasons why research in this field is crucial for organisations aiming to leverage AI technology effectively.

The following are the significant factors

1. Understanding Adoption Challenges: Research helps identify and understand the challenges associated with the adoption of AI-based decision making. It provides insights into the barriers that organisations face, such as technological readiness, cultural resistance, and ethical concerns. By examining these challenges, researchers can develop strategies to overcome them and facilitate successful adoption (Duan, Edwards and Dwivedi, 2019a).

2. Optimising Implementation Strategies: Through research, organisations can gain insights into the most effective strategies for implementing AI-based decision making. It helps identify the necessary steps, resources, and processes required to integrate AI technologies into existing organisational systems (Henrique et al., 2020). By understanding the best practices, organisations can optimise their implementation efforts and achieve desired outcomes.
3. Enhancing Decision-Making Capabilities: Research in this area allows for the advancement and improvement of AI-based decision-making capabilities. By studying the algorithms, models, and techniques used in AI decision-making systems, researchers can develop innovative approaches to enhance accuracy, efficiency, and reliability. This can lead to better-informed decisions, improved productivity, and enhanced business performance (Duan, Edwards and Dwivedi, 2019b).
4. Mitigating Risks and Ethical Concerns: The adoption of AI-based decision making comes with potential risks and ethical considerations. Research plays a crucial role in addressing these concerns by identifying and developing methods to mitigate biases, ensure transparency, and address privacy and security issues (Jobin, Ienca and Vayena, 2019). By understanding the ethical implications, researchers can guide the development and adoption of AI systems that align with ethical standards and regulatory requirements.
5. Enabling Informed Decision-Making: Research in this field provides organisations with the knowledge and evidence necessary to make informed decisions about adopting AI-based decision-making systems. It offers insights into the benefits, risks, costs, and potential return on investment (ROI) associated with AI adoption. This information enables organisations to assess the feasibility and strategic value of implementing AI technologies (Duan, Edwards and Dwivedi, 2019b).

The following were the outcomes of the Research

- The study will find a gap in the present body of knowledge regarding India's Intelligent decision support system. This study will be of great use to academicians

- This study will aim at finding factors that will aid companies' adoption of intelligent decision support systems that will, in turn, help the corporate industry in developing the product.
- It will help in making near to perfect decisions that will help in boosting trade and commerce of the industry at large
- Finally, the government may use data from the research to help the county's economy and make India compete globally.

Research on the adoption of artificial intelligence-based decision making is vital for organisations aiming to harness the potential of AI technology effectively. By understanding the challenges, optimising implementation strategies, enhancing decision-making capabilities, mitigating risks, and enabling informed decision-making, research in this field empowers organisations to make informed choices and leverage AI-based decision-making systems to drive innovation and achieve competitive advantage.

1.7 The study

Intelligent Decision Support Systems (IDSS) have gained significant attention as powerful tools that assist organisations in making informed and data-driven decisions. The adoption of IDSS can lead to improved decision-making processes, enhanced productivity, and better overall organisational performance. This essay explores the factors that influence the adoption of IDSS and analyses them through the Technological, Organizational, and Environmental (TOE) framework.

1. Technological Factors: Technological factors play a crucial role in the adoption of IDSS. These factors include the technological capabilities and features of the system, data availability and quality, ease of use, and compatibility with existing IT infrastructure. Organisations must evaluate the technological readiness of their systems and ensure that the IDSS aligns with their technological requirements (Kettinger, Teng and Guha, 1997).
2. Organisational Factors: Organisational factors encompass the internal characteristics of an organisation that influence the adoption of IDSS. These factors include organisational culture, leadership support, employee readiness, and the availability of resources. A supportive organisational culture that promotes data-driven decision

making and encourages innovation is crucial for successful adoption. Additionally, effective leadership that champions the adoption of IDSS and provides necessary resources and training is essential (Chau, Tam and Tam, 2014).

3. Environmental Factors: Environmental factors refer to external influences on IDSS adoption. These factors include market dynamics, competitive pressures, regulatory requirements, and the availability of external support and expertise. Organisations need to assess the external environment and consider how these factors impact the adoption of IDSS. Adapting to changing market trends and understanding the competitive landscape can contribute to successful adoption (Kettinger, Teng and Guha, 1997).

Adopting Intelligent Decision Support Systems (IDSS) can provide organisations with a competitive advantage by enabling data-driven decision making and enhancing overall organisational performance. However, the successful adoption of IDSS requires careful consideration of various factors. The Technological, Organizational, and Environmental (TOE) framework provides a comprehensive perspective for analysing these factors. By evaluating technological capabilities, addressing organisational readiness, considering environmental influences, focusing on user acceptance, and assessing economic implications, organisations can effectively adopt and leverage IDSS to drive innovation and improve decision-making processes.

1.8 Conclusion

Artificial Intelligence and machine learning have revolutionized various aspects of human life, including decision-making. Decision-making involves identifying and choosing alternatives based on the decision-maker's values and preferences. However, professionals in organizational decision-making often face challenges due to their limited data and emotional factors. AI-powered decision-making has become a game-changer, as it considers all available information and is objective.

Big data is a significant challenge in decision-making, with 99.5% of acquired data never used or examined. Big data analytics and business intelligence are becoming popular due to the massive data expansion. AI models and algorithms drive decision-making by systematically extracting relevant data from data, making predictions, projections, and interpretations. AI finds new ways to enhance our lives, such as self-driving cars, medical detection, and online shopping.

AI-driven business intelligence is the future, as data has powered businesses for decades. It helps business people make decisions and provides customer insights. However, the brain cannot digest all facts, so AI and business intelligence decision-making help. AI can learn data modelling, accurately classify data, forecast, categorize, and suggest in real-time, improving business choices.

The Intelligent decision support system is a promising solution for business decision-making, offering benefits such as business automation, customer relationship management (CRM), high ROI, and better decisions. However, there are challenges in extracting and analyzing data, such as human psychological flaws and the need for data-driven decision-making.

The research aims to understand the factors influencing the adoption of AI-based decision making and Intelligent Decision Support Systems (IDSS) in India. Key factors include technological capabilities, organizational readiness, user acceptance, economic factors, and differences in adoption across different industries or organizations. The study will focus on whether small and medium enterprises in India will adopt IDSS, what factors would enable them to adopt the technology, and what would not.

The significance of this research lies in its ability to identify adoption challenges, optimize implementation strategies, enhance decision-making capabilities, mitigate risks and ethical concerns, and enable informed decision-making. The research proposal will identify gaps in knowledge regarding India's Intelligent decision support system, aid companies in adopting IDSS, boost trade and commerce, and potentially help the government use data from the research to help the country's economy and make India compete globally.

The Technological, Organizational, and Environmental (TOE) framework will be used to analyze the factors influencing IDSS adoption. Technological factors include the system's capabilities, data availability, quality, ease of use, compatibility with existing IT infrastructure. Organizational factors include organizational culture, leadership support, employee readiness, and resource availability. Environmental factors include market dynamics, competitive pressures, regulatory requirements, and external support and expertise.

Adopting IDSS can provide organizations with a competitive advantage by enabling data-driven decision making and enhancing overall organizational performance. However, successful adoption requires careful consideration of various factors. The TOE framework provides a comprehensive perspective for analyzing these factors, allowing organizations to effectively adopt and leverage IDSS to drive innovation and improve decision-making processes.

CHAPTER II
LITERATURE REVIEW

1.1 Introduction

The Past, Present and future of IDSS

The history and evolution of intelligent decision support systems (IDSS) can be traced back to the development of decision support systems (DSS) in the field of computer science. DSS are computerized information systems that support decision-making activities (Daniel J. Power, Ramesh Sharda and Burstein, 2005). Over time, DSS research and practice have evolved into various sub-groupings, including personal decision support systems, group support systems, negotiation support systems, intelligent decision support systems, knowledge management-based DSS, executive information systems/business intelligence, and data warehousing (Arnott and Pervan, 2005). One of the sub-groupings that emerged is intelligent decision support systems, which combine DSS with artificial intelligence (AI) technology (Najjar, Amro and Macedo, 2021).

Intelligent decision support systems (IDSS) are systems supported by information science and modern management science that help executives make better decisions (Yang, 2023). They employ AI techniques to generate decision alternatives and assist decision-makers in solving structured, semi-structured, or unstructured problems (Najjar, Amro and Macedo, 2021). IDSS can be used to assist decision-makers in solving structured, semi-structured, or unstructured problems (Najjar, Amro and Macedo, 2021). They are designed to provide decision support in various domains, including finance, recruitment, and emergency management (Fertier *et al.*, 2020; Najjar, Amro and Macedo, 2021; Zhao and Saeed, 2022a).

The types of IDSS at present include communications-driven, data-driven, document-driven, knowledge-driven, and model-driven systems (Daniel J. Power, Ramesh Sharda and Burstein, 2005). These types of IDSS differ in terms of their functionality and the way they support decision-making activities. Communications-driven IDSS focus on facilitating communication and collaboration among decision-makers. Data-driven IDSS emphasize the use of data analysis and visualization techniques to support decision-making. Document-driven IDSS focus on managing and organizing documents relevant to decision-making. Knowledge-driven IDSS leverage knowledge management techniques to support decision-making. Model-driven IDSS use mathematical models and simulations to support decision-making (Daniel J. Power, Ramesh Sharda and Burstein, 2005).

In the future, IDSS are expected to continue evolving and advancing with the development of AI and other technologies. The integration of AI and machine learning in organizations is seen as a source of value creation and can contribute to digital transformation (Kitsios and Kamariotou, 2021). The use of big data analytics and predictive modeling techniques can enhance the capabilities of IDSS in understanding, predicting, and responding to future events (Sheng *et al.*, 2020).

IDSS in business

The concept of intelligent decision support systems gained traction in the early 2000s with the advent of advanced technologies such as data mining and metaheuristics (B, Vinagre and Cortez, 2015). These technologies enabled the development of IDSS that could leverage AI techniques to provide more sophisticated decision support. The field of business intelligence (BI) also played a significant role in the evolution of IDSS, as it focused on utilizing data analysis and visualization techniques to support decision-making (Visinescu, Jones and Sidorova, 2016).

One of the key motivations behind the development of IDSS in business was the need to handle complex and unstructured decision-making scenarios. Traditional decision support systems were limited in their ability to handle such scenarios, which led to the integration of AI techniques in IDSS to address these challenges (Zhao and Saeed, 2022a). The use of AI, including techniques such as artificial neural networks, allowed IDSS to analyze large volumes of data, identify patterns, and generate insights to support decision-making (Zhao and Saeed, 2022a).

The evolution of Intelligent Decision Support Systems (IDSS) in business has been significantly influenced by technological advancements and the availability of big data. The utilization of sophisticated data analytics techniques has opened up new avenues for IDSS to extract valuable insights and enhance decision-making processes. Moreover, the integration of geospatial analysis and remote sensing has further broadened the capabilities of IDSS, enabling businesses to make informed decisions with spatial considerations (Jia *et al.*, 2022).

In crisis situations and emergency management, IDSS have emerged as crucial tools due to their ability to process real-time data and provide contextualized information for decision-making. Governments and organizations have increasingly relied on IDSS to analyze data, model crisis scenarios, and make well-informed decisions during emergencies (Duah, Ford and Syal, 2014).

Looking ahead, the future of IDSS in business is poised for further evolution with the integration of artificial intelligence (AI), machine learning, and big data analytics. These advancements will empower IDSS to offer more precise predictions, optimize decision-making processes, and bolster strategic decision-making. The development of context-aware IDSS, which take into account geospatial elements and user preferences, will enhance the personalization and location-specific decision support provided by IDSS (Jia *et al.*, 2022).

1.2 Conceptual framework

The Technology-Organization-Environment (TOE) framework

The Technology-Organization-Environment (TOE) framework is a widely used model for understanding the factors that influence the adoption of technology innovation in organizations. This framework considers three key factors: technology, organization, and environment. Within each of these factors, there are several subheadings that further explore the specific elements that impact adoption. In this essay, we will delve into each subheading and explain its significance in the TOE framework, drawing on recent citations from the past five years.

1. Technology

a. Complexity: The complexity of a technology refers to its level of difficulty in understanding and using it. (Alshamaila, Papagiannidis and Li, 2013) highlight the importance of considering the impact of technological characteristics on adoption.

b. Compatibility: Compatibility refers to the extent to which a technology aligns with the existing systems, processes, and values of an organization. (Gangwar, Date and Ramaswamy, 2015) argue that the TOE framework lacks major constructs in the model and variables in each context, limiting its explanatory power in technology adoption.

c. Relative advantage: Relative advantage refers to the perceived benefits and advantages of adopting a technology compared to existing alternatives. (Alraja *et al.*, 2022) highlight that the TOE framework offers a balance of internal and external drivers to help organizations effectively implement innovations.

2. Organization

a. Firm size: Firm size refers to the size and scale of an organization. (Tian *et al.*, 2021) argue that the TOE framework, with its focus on technological, organizational, and environmental contexts, is applicable in the current situation characterized by the increasing use of digital technologies and intensive competition.

b. Technological readiness: Technological readiness refers to the organization's preparedness to embrace and utilize new technologies effectively, while organizational readiness pertains to the internal structures, processes, and capabilities that support technology adoption (Awuah, Onumah and Duho, 2021).

c. Top management support: Top management support refers to the endorsement and active involvement of senior leaders in the adoption process. (Alraja *et al.*, 2022) emphasize that the TOE framework offers the right balance of internal and external drivers to help organizations effectively implement innovations.

3. Environment

a. Competitive pressure: Competitive pressure refers to the influence of market competition on the adoption of technology. (BUGAWA, Al-Harbi and Mahamid, 2018) highlight the TOE framework as a powerful tool for analyzing the basic factors when employing new technology in an organization.

b. Stakeholder influence: Stakeholder influence refers to the impact of external stakeholders, such as customers, suppliers, and regulators, on the adoption of technology. (Almunawar *et al.*,

2022) mention the TOE framework's identification of three key factors that influence firms' adoption of technology innovation: technology, organization, and environment.

c. Supplier efficacy: Supplier efficacy refers to the capabilities and effectiveness of technology suppliers in supporting the adoption process. (Wallace *et al.*, 2020) propose an extended TOE framework specifically aimed at cybersecurity, which includes dimensions such as cyber catalysts and practice standards.

d. Government support: Government support refers to the policies, regulations, and incentives provided by the government to promote technology adoption. (Gutierrez, Boukrami and Lumsden, 2015) use the TOE framework to determine the factors influencing managers' decision to adopt cloud computing in the UK.

In conclusion, the TOE framework provides a comprehensive model for understanding the factors that influence the adoption of technology innovation in organizations. It considers the technological, organizational, and environmental contexts and explores various subheadings such as complexity, compatibility, trialability, relative advantage, observability, firm size, employee cooperation, top management support, competitive pressure, stakeholder influence, supplier efficacy, and government support. While some criticisms have been raised regarding the framework's explanatory power, it remains a widely used and valuable tool for analyzing technology adoption.

Expert or knowledge-based Intelligent decision support system architecture

The following is the Expert or knowledge-based Intelligent decision support system architecture cited by (Tariq and Rafi, 2012)

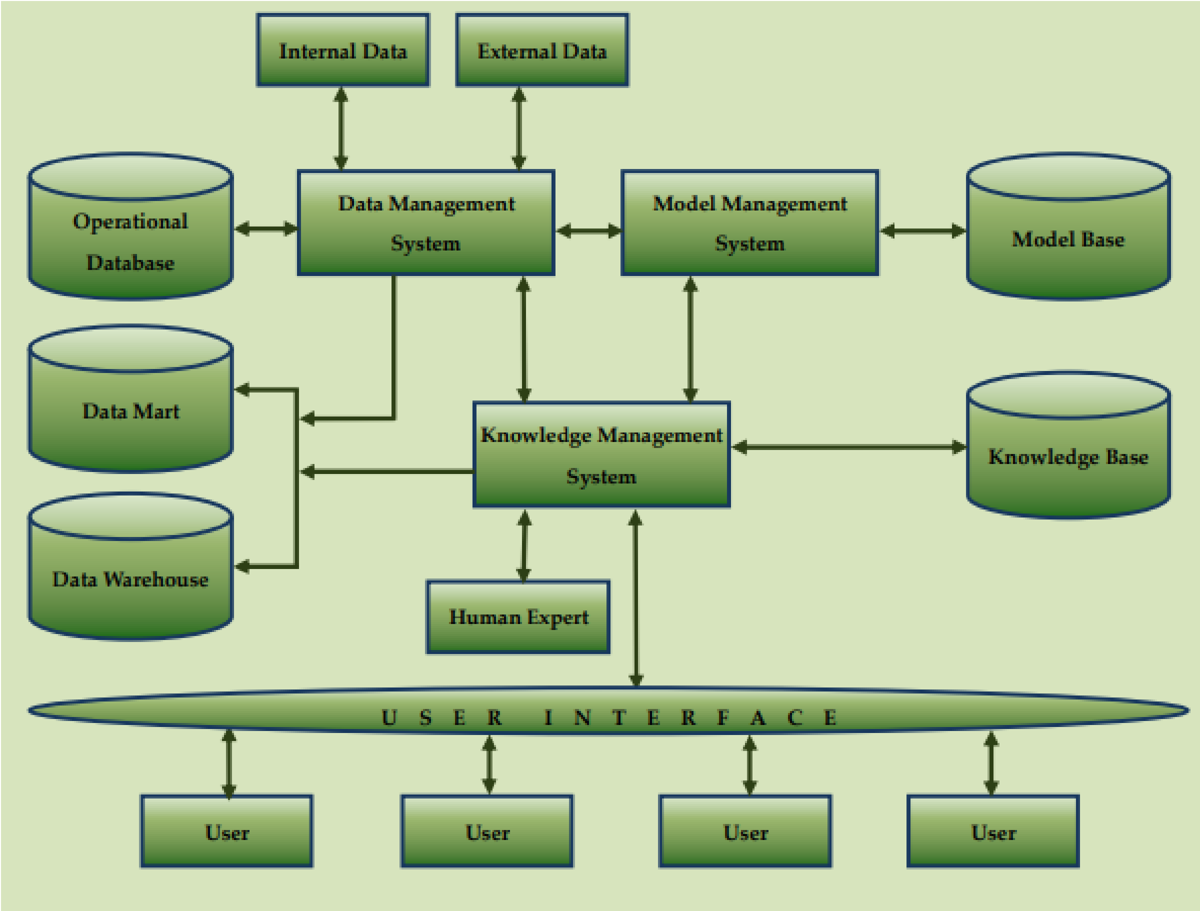

Figure 1 Knowledge based or expert based Intelligent decision support system by Tariq and Rafi, 2012 model

To assist decision-makers, the present decision support systems only manipulate data and model, and it does not serve as the decision-makers intelligent assistant (Tariq and Rafi, 2012). Recently, the Decision support system field has seen significant advancements thanks to the incorporation of artificial intelligence tools and technologies, such as knowledge bases, Natural language, genetic algorithms, multi-agent systems, fuzzy logic, neural networks, and so forth. (Tariq and Rafi, 2012)

Domain knowledge, modeling, and analytic systems are being used by Decision Support systems to give users the option of intelligent assistance (Tariq and Rafi, 2012). Knowledge base subsystems are used to formulate, model, analyze, and interpret the results of the problems(Tariq and Rafi, 2012).

A Decision Support System consists of three essential parts.

• Database management subsystems: It consists of a database with information pertinent to the category of issues for which the Decision Support System was created (Tariq and Rafi, 2012). Datawarehouse and Database Management Subsystem can communicate with one another and/or the organization's data marts(Tariq and Rafi, 2012). Users are separated from the technical features of the database by a DBMS database processing and structure(Tariq and Rafi, 2012). Additionally, it should be able to tell the user of the different types of data that are accessible and how to access them(Tariq and Rafi, 2012).

• Model Management Subsystem: A Model Base Management Subsystem performs a function similar to a Data Base Management System(Tariq and Rafi, 2012). It features a model base, which includes models for Decision Support Systems that include financial, statistical, management science, and others that have the capacity for analysis. Additionally, a Model base Management System's function is to transform data from a Data Base Management System into information via analyzing it with models(Tariq and Rafi, 2012).

• User Interface Subsystem: It addresses every facet of interaction between a user and various Decision Support systems' component parts(Tariq and Rafi, 2012). Decision Support systems must be user-friendly because many of their users are managers who are not computer literate(Tariq and Rafi, 2012). Built with user-friendly interfaces that are intuitive t these interfaces provide model construction and engagement with the model, including getting advice and insight from it(Tariq and Rafi, 2012).

A Knowledge Management Subsystem is included in an Intelligent DSS in addition to the previously listed elements.

• Knowledge Management Subsystem: Following the identification, gathering, and management of the information, knowledge must be transformed (Tariq and Rafi, 2012). This calls for categorization, analysis, and synthesis, all of which is human involvement, as technology cannot produce knowledge(Tariq and Rafi, 2012). Only an individual may create information into a structure that makes it simple for another person to turn it into knowledge upon retrieval (Tariq and Rafi, 2012). There must be caution against collecting all available knowledge or information without assurance that it will be profitable because not all knowledge is equal (Tariq and Rafi, 2012).

There are various sources of information and knowledge that can be broadly categorized as both internal and external (Tariq and Rafi, 2012). Operational databases, data warehouses, data marts, and people are examples of internal sources working for a company. While external sources include vendors, clients, competitors, the government internet, agencies, etc. (Tariq and Rafi, 2012)

Small and Medium Enterprises' (SMEs) role in the Indian economy

Small and Medium Enterprises (SMEs) play a crucial role in the Indian economy, contributing significantly to its growth and development. In India, SMEs are classified into two categories: manufacturing enterprises and service enterprises (Gupta, Guha and Krishnaswami, 2013). These enterprises are defined by the Micro, Small and Medium Enterprises Development Act of 2006 (Gupta, Guha and Krishnaswami, 2013). SMEs in India are characterized by their relatively small size, limited resources, and lower levels of capital investment compared to large-scale enterprises (Karadakal, Goud and Thomas, 2015).

SMEs in India have a significant impact on various aspects of the economy. They contribute to employment generation, accounting for a substantial portion of the industrial units in the country (Karadakal, Goud and Thomas, 2015). SMEs are responsible for creating job opportunities and reducing unemployment rates, particularly in rural areas (Socrates and B. V. Gopalakrishna, 2020). They also contribute to the country's exports, with approximately 40% of India's exports being attributed to SMEs (Karadakal, Goud and Thomas, 2015). Additionally, SMEs contribute to the Gross Domestic Product (GDP) of India (Paliwal, Chandra and Sharma, 2020). Their contribution to the economy is vital for promoting economic growth, inclusive development, and poverty alleviation (Etuk, Etuk and Michael, 2014).

The growth and development of SMEs in India are influenced by various factors. One such factor is the implementation of a green organizational culture, which is still in its early stages among SMEs in India (Subramanian and Suresh, 2023). The adoption of environmentally friendly practices can enhance the competitiveness and sustainability of SMEs. However, there are challenges in terms of resource constraints and limited awareness among SME owners/managers regarding the benefits of green practices (Subramanian and Suresh, 2023).

Another factor that affects the growth of SMEs in India is the level of formalization of human resource management practices. Many SMEs in India face challenges in effectively managing their human resources due to limited resources and a lack of awareness about best practices (Singh and Vohra, 2009). Improving the formalization of human resource management can enhance the productivity and performance of SMEs.

Access to finance is another critical factor that affects the growth and development of SMEs in India. Many SMEs face challenges in accessing affordable credit and financial services (Korang and Golly, 2021). Limited access to finance hampers their ability to invest in technology, expand operations, and innovate. Therefore, improving access to finance for SMEs is crucial for their growth and development.

Furthermore, SMEs in India face challenges related to succession planning and business continuity. Many SMEs are family-owned, and the lack of proper succession planning can lead to disruptions in business operations (Jain and Jain, 2014). Developing effective succession planning strategies can ensure the continuity and long-term sustainability of SMEs.

1.3 Artificial intelligence versus humans in decision making

Literature Review found the following differences between Artificial intelligence and humans in decision making. Some of them are an advantage over humans and some of them are a disadvantage.

- Replace human intelligence
- Data processing in real time
- Analytical capabilities
- Prediction capabilities

Replace human intelligence

Huang and Rust (2018) discuss the growing utilization of AI in service industries and its impact on human jobs. They highlight examples such as robots automating various tasks in homes, healthcare, hotels, and restaurants, as well as virtual bots replacing customer service representatives. The authors also mention the use of AI applications to replace portfolio managers and social robots replacing human greeters in customer-facing services.

In their study, Huang and Rust (2018) develop a theory of AI job replacement that addresses the impact of AI on service tasks. They identify four intelligences required for service tasks:

mechanical, analytical, intuitive, and empathetic. The authors propose that firms should decide between humans and machines based on these intelligences when assigning tasks.

The concern of AI completely replacing humans is also discussed in the literature. Huang and Rust (2018) mention the singularity concern, where AI becomes dominant over humans in all forms of intelligence. This concern is shared by prominent figures such as Stephen Hawking and Bill Gates (Huang and Rust, 2018).

Shi et al. (2023) explore the relationship between AI and human intelligence, particularly the possibility of AI overtaking or replacing humans. They introduce the concept of hybrid human-artificial intelligence (H-AI), which combines human abilities and AI capabilities. The authors discuss the impact of AI on various aspects of life, including business, and the need to understand the dynamics between AI and human intelligence.

Xiong (2023) acknowledges that AI can perform tasks that require human intelligence but emphasizes that AI cannot replace human care, thinking, and interaction. The author suggests that AI can increase the productivity of leaders by taking over automated and administrative activities.

Real-Time Advantage of Artificial Intelligence over Humans in Business Decision Making

In the realm of business decision-making, the integration of artificial intelligence (AI) has been a transformative force, offering real-time advantages over human decision-making processes. As highlighted by (Soleimani *et al.*, 2021), the adoption of decision support tools like AI is increasingly crucial for managers seeking optimal outcomes. Decision Support

Systems (DSS), Business Intelligence (BI), and AI are instrumental in enhancing the decision-making process by providing valuable insights and analysis (Soleimani *et al.,* 2021) further emphasizes the significance of AI in business efficiency, noting that AI enables access to vast amounts of data and facilitates real-time analysis in the cloud, thereby offering instantaneous information support for managerial decisions.

The potential of AI to revolutionize business decision-making is underscored by the insights from 'A Survey on Business Intelligence Approach Based on Deep Learning' (2023). This study, along with previous research by Dursane (2018), accentuates the advantages and limitations associated with leveraging business intelligence and analytics in decision-making processes ("A Survey on Business Intelligence Approach Based on Deep Learning", 2023). Moreover, the study by (Hamad *et al.,* 2020) sheds light on the positive impact of business intelligence on decision-making within academic libraries, indicating that BI enhances the accuracy and timeliness of decisions made by library decision-makers.

In the context of AI's capabilities, Carnà et al. (2022) elaborate on how AI operates on algorithms that empower machines to engage in reasoning, problem-solving, object recognition, word recognition, inference of world states, and decision-making. This underscores the potential of AI to outperform humans in certain aspects of decision-making, particularly in scenarios where rapid analysis and processing of vast datasets are required. By harnessing AI technologies, businesses can gain a competitive edge by making data-driven decisions in real-time, leveraging the speed and accuracy that AI offers over traditional human decision-making processes.

The real-time advantage of AI over humans in business decision-making lies in its ability to swiftly process and analyze massive volumes of data, identify patterns, and generate insights at a pace that surpasses human cognitive capabilities. AI systems can continuously learn and adapt based on new information, enabling businesses to make agile decisions in dynamic environments. This agility is crucial in today's fast-paced business landscape, where timely decisions can mean the difference between success and failure.

Analytical Capabilities of Artificial Intelligence Compared to Humans in Decision Making

In the realm of business decision-making, the analytical capabilities of artificial intelligence (AI) have been a subject of increasing interest and scrutiny. The comparison between AI and human decision-making processes has been a focal point in recent literature, shedding light on the strengths and limitations of each approach. Shrestha, Ben-Menahem and Krogh (2019) delve into the intricacies of decision-making structures in the era of AI, highlighting key factors that differentiate human and AI-based decision-making. These factors include the specificity of the decision search space, interpretability of the decision-making process and outcome, size of the alternative set, decision-making speed, and replicability.

Trunk, Birkel and Hartmann (2020) further contribute to this discourse by exploring the integration of human and artificial intelligence in strategic organizational decision-making. Their systematic literature review and content analysis offer insights into the current landscape of combining AI with human decision-making processes, particularly in scenarios characterized by uncertainty. By synthesizing existing research, the authors provide a comprehensive overview of the opportunities and challenges associated with leveraging AI for organizational decision-making, highlighting the potential synergies that can arise from the collaboration between human expertise and AI analytical capabilities.

The transformative impact of AI on business decision-making is underscored by Rajaonson and Schmitt (2024), who discusses the role of AI and data technologies in advancing sustainable development goals. The author emphasizes how AI, machine learning, natural language processing, the Internet of Things, and other data-driven analytical techniques are reshaping industries by offering advanced data analysis, automation, and data-driven decision-making capabilities. This highlights the profound influence that AI-powered analytics have on enhancing decision-making processes within organizations, enabling them to harness the power of data for strategic insights and informed choices.

Prasanth et al. (2023) further elaborate on the significance of AI in revolutionizing business decision-making. Their study emphasizes how AI has become a cornerstone in enabling organizations to extract valuable insights from vast datasets, thereby enhancing their decision-making processes. By leveraging AI's advanced analytical capabilities, organizations can navigate complex data landscapes more effectively, leading to more informed and data-driven decisions. This underscores the pivotal role that AI plays in augmenting human decision-making by providing sophisticated analytical tools and techniques.

However, amidst the advancements and benefits that AI brings to business decision-making, Booyse and Scheepers (2023) sheds light on the barriers that organizations face in adopting automated decision-making processes through AI. The author points out that AI may prioritize quantitative aspects over qualitative elements in decision-making, posing challenges in balancing the analytical rigor of AI with the nuanced judgment and contextual understanding that humans bring to the table. This highlights a critical consideration in the integration of AI into decision-making processes, emphasizing the importance of addressing potential biases and limitations that AI-driven analytics may introduce.

Predictive Capabilities of Artificial Intelligence Compared to Humans in Decision Making

Artificial intelligence (AI) has demonstrated remarkable predictive capabilities in decision making, often outperforming humans in various domains.

In the healthcare domain, Rajkomar et al. (2018) explored the use of deep learning with electronic health records (EHR) for accurate and scalable predictions. Their study demonstrated that deep learning models using EHR data achieved high accuracy in predicting medical events such as in-hospital mortality, unplanned readmission, and length of stay. The models outperformed traditional predictive models and showed potential for personalized medicine and improved healthcare quality.

Predictive capabilities of AI extend beyond healthcare. (Sicard *et al.*, 2023) discussed the use of predictive techniques, including empirical, mechanistic, and data-driven approaches, in optimizing food and bioresources transformation processes. The authors highlighted the advantages and limitations of current techniques and emphasized the potential of AI-based predictive modeling in guiding changes and influencing decision making in the food industry.

1.4 Advantages of artificial intelligence in decision making

- Automation
- Competitive edge
- Sustainability
- Research and development
- Personalized recommendation
- Continuous learning
- Lack of bias
- Scalability
- Enhanced customer experience
- Resource allocation

Automation

Artificial intelligence (AI) offers several advantages in decision-making processes in business, one of which is automation. Automation refers to the ability of AI systems to perform tasks and make decisions without human intervention. This can streamline processes, increase efficiency, and reduce the potential for human error.

Automation in decision-making, particularly through the utilization of prediction technology in AI systems, has significantly transformed various industries by enabling accurate predictions for enhancing decision-making processes (Lecun, Bengio and Hinton, 2015). These advancements have led to improved outcomes in fields such as healthcare diagnostics, where AI systems have demonstrated superior accuracy compared to human capabilities (Lecun, Bengio and Hinton, 2015). However, the integration of AI in decision-making processes also introduces challenges related to human-AI interaction, bias mitigation, and ethical considerations (Jumper *et al.*, 2021).

The ethical implications of automated decision-making, particularly in scenarios with significant impacts on individuals, emphasize the importance of ensuring fairness, explainability, and compliance with regulations such as the General Data Protection Regulation (Singh, Cobbe and Norval, 2019).

The advantages of automation in decision-making using AI are not limited to specific industries. Studies have shown that AI and fuzzy logic tools can be universally applied to support decision-making under conditions of uncertainty in various business environments (Bogachov *et al.*, 2020). By utilizing AI, businesses can make objective and well-grounded decisions, taking into account environmental factors and minimizing the impact of uncertainty.

Competitive edge

Artificial intelligence (AI) provides businesses with a competitive edge in decision-making processes. By leveraging AI technologies, companies can gain valuable insights, make data-driven decisions, and stay ahead of their competitors.

One way AI contributes to a competitive advantage is through its ability to analyze large amounts of data quickly and accurately. AI algorithms can process vast datasets and identify patterns, trends, and correlations that may not be apparent to human decision-makers (Bogachov *et al.*, 2020). This enables businesses to make more informed decisions based on comprehensive and objective analyses of data.

Moreover, AI can enhance decision-making in the area of human resources (HR), which is crucial for maintaining a competitive advantage. The quality and skills of employees are key factors in a company's success, and AI can assist in making HR-related decisions based on objective data rather than subjective considerations (Fallucchi *et al.*, 2020). For example, AI can be used to predict employee attrition, identify high-potential candidates for promotion, and optimize workforce planning (Fallucchi *et al.,* 2020). By leveraging AI in HR decision-making, companies can ensure they have the right talent in place to drive their competitive advantage.

Furthermore, the adoption of AI technologies, coupled with information technology (IT) capabilities, can mediate the relationship between AI and competitive advantage (Awamleh and Bustami, 2022). By effectively integrating AI into their IT infrastructure, companies can harness the power of AI to optimize their operations, improve efficiency, and gain a competitive edge (Awamleh and Bustami, 2022). This integration allows businesses to leverage AI across various functions, such as supply chain management, customer relationship management, and decision support systems, to enhance their overall performance and competitiveness.

Research and development (R&D) is a significant advantage of decision-making using artificial intelligence (AI) in business

Research and development (R&D) is a significant advantage of decision-making using artificial intelligence (AI) in business. AI technologies can support and enhance the R&D process, leading to improved innovation, efficiency, and competitiveness.

One key advantage of AI in R&D decision-making is its ability to analyze and process vast amounts of data quickly and accurately. AI algorithms can identify patterns, trends, and correlations in large datasets, enabling businesses to gain valuable insights and make data-driven decisions in their R&D efforts (Bogachov *et al.,* 2020). This can help companies identify new opportunities, optimize product development, and enhance the effectiveness of their R&D strategies.

Moreover, AI can assist in the discovery and development of new products and technologies. By leveraging AI-powered algorithms and machine learning techniques, businesses can automate the process of generating and evaluating new ideas, predicting market demand, and identifying potential areas for innovation (Bogachov *et al.,* 2020). This can accelerate the R&D process, reduce costs, and increase the likelihood of successful product development.

Customized or personalized recommendation is a significant advantage of decision-making using artificial intelligence (AI) in business

Customized or personalized recommendation is a significant advantage of decision-making using artificial intelligence (AI) in business. AI technologies can analyze vast amounts of data and generate personalized recommendations tailored to individual preferences and needs. This personalized approach can enhance customer experiences, increase customer satisfaction, and drive business growth.

One area where personalized recommendation is valuable is in the e-commerce industry. AI-powered recommendation systems can analyze customer browsing and purchase history, as well as demographic and behavioral data, to provide personalized product recommendations (Ameen *et al.,* 2021). These recommendations can help customers discover relevant products, improve their shopping experience, and increase the likelihood of making a purchase. By leveraging AI in recommendation systems, businesses can enhance customer engagement, increase sales, and build customer loyalty.

Furthermore, personalized recommendation can extend beyond product recommendations to include next-best action recommendations. AI can analyze customer demographics, behaviors, and interactions to generate personalized recommendations for the next best action or decision (Cao and Zhu, 2022). This can be valuable in various domains, such as automated decision-making in business, where AI can provide personalized recommendations for optimal actions based on individual circumstances and goals (Cao and Zhu, 2022).

Continuous learning is a significant advantage of decision-making using artificial intelligence (AI) in business

Continuous learning is a significant advantage of decision-making using artificial intelligence (AI) in business. AI systems have the ability to continuously learn and improve their performance over time, allowing businesses to adapt to changing environments, make more informed decisions, and stay ahead of the competition.

One key aspect of continuous learning in AI is reinforcement learning. Reinforcement learning algorithms enable AI systems to learn from interactions with the environment and receive feedback in the form of rewards or penalties (Mnih *et al.*, 2015). Through this iterative process, AI systems can continuously update their decision-making strategies and improve their performance based on past experiences.

Moreover, continual learning in AI can address the challenge of forgetting previous knowledge when learning new tasks. Existing research in continual learning focuses on avoiding catastrophic forgetting, where the AI system loses previously learned knowledge when learning new tasks (Gao, Ascoli and Zhao, 2021). By developing memory mechanisms and learning algorithms that balance persistence and transience of knowledge, AI systems can retain important information while adapting to new tasks, leading to more efficient and robust decision-making (Gao, Ascoli and Zhao, 2021).

The lack of bias is an advantage of decision-making using artificial intelligence (AI) in business

The lack of bias is an advantage of decision-making using artificial intelligence (AI) in business. AI systems have the potential to reduce bias and promote fairness in decision-making processes.

Research by (Caliskan, Bryson and Narayanan, 2017) demonstrates that biases present in human language can be reflected in AI systems trained on text corpora. However, this awareness of biases in AI systems can also be leveraged to identify and address sources of bias in culture, including technology. By recognizing and understanding these biases, businesses can take steps to mitigate them and ensure fair decision-making processes.

Moreover, (Almpani, Stefaneas and Frangos, 2023) discuss the importance of ethical decision-making in AI systems and the need to ensure correct ethical behavior. They emphasize the consideration of societal and moral norms, transparency, and safety in AI decision-making processes. By incorporating ethical principles and guidelines into AI systems, businesses can mitigate biases and promote fair decision-making.

Business scalability is an advantage of decision-making using artificial intelligence (AI) in business

Artificial intelligence (AI) has become a pivotal tool in modern business operations, offering a myriad of advantages to organizations that leverage its capabilities. One of the key benefits of utilizing AI in decision-making processes within businesses is the enhancement of scalability. Scalability, as defined by , refers to the ability of a business process to accommodate growth in the number of processes or expand its operations efficiently (Yaqin, Sarno and Fauzan, 2017). This scalability is crucial for businesses looking to adapt to changing market dynamics, customer demands, and operational requirements. The integration of AI technologies, particularly machine learning (ML), as highlighted by , plays a significant role in enhancing a company's scalability and improving overall operations (Sanil *et al.*, 2021).

The scalability afforded by AI in business decision-making is not limited to internal processes but extends to the broader business ecosystem. discusses how crowdsourcing platforms benefit from scalability, enabling them to grow rapidly, expand with minimal additional costs, and generate substantial revenue (Köhler, 2017). This scalability in crowdsourcing platforms showcases how AI-driven decision-making can have far-reaching implications for various business models, facilitating growth and sustainability in competitive markets.

Moreover, the advent of AI technologies, as emphasized by , has propelled the concept of being "AI First" for enterprises, revolutionizing traditional business practices and opening new avenues for optimizing decision-making processes and operational efficiency (Lahlali, Berbiche and Alami, 2021). By embracing AI as a core component of their operations, businesses can not only enhance their scalability but also stay ahead of the curve in a rapidly evolving digital landscape.

In the realm of decision-making frameworks, advocate for an AI-driven approach that prioritizes business strategy as a fundamental driver. This strategic alignment ensures that AI is utilized to address pertinent business challenges, fostering innovation and competitive advantage within organizations (Gudigantala, Madhavaram and Bicen, 2023). By integrating AI decision-making frameworks that are aligned with business objectives, companies can maximize the value derived from AI technologies, further enhancing their scalability and operational effectiveness.

In conclusion, the utilization of AI in business decision-making processes offers a transformative advantage in terms of scalability. By harnessing the power of AI technologies such as machine learning, businesses can adapt to changing environments, expand their operations efficiently, and drive innovation across various sectors. The scalability enabled by AI not only enhances internal processes but also extends to the broader business ecosystem, empowering organizations to thrive in competitive markets and achieve sustainable growth.

Enhanced customer experience is a significant advantage of decision-making using artificial intelligence (AI) in business.

Enhanced customer experience is a significant advantage of decision-making using artificial intelligence (AI) in business. AI technologies can analyze customer data, preferences, and behaviors to provide personalized and tailored experiences, leading to improved customer satisfaction and loyalty.

The use of AI in various sectors, such as retail and financial services, has been shown to bridge the gap between brands and customers, transforming the overall customer experience (Hossain *et al.*, 2022). Additionally, AI plays a significant role in influencing customer perceptions and decision-making processes, ultimately enhancing value co-creation and customer engagement (Chen *et al.*, 2022).

Studies have highlighted that AI can lead to enhanced customer experiences by providing real-time data analysis, personalized recommendations, and predictive insights, thereby improving overall customer satisfaction (Koo *et al.*, 2021). Furthermore, the integration of AI in customer analytics capabilities has been shown to provide substantial competitive advantages for firms by offering real-time solutions and valuable customer insights (Klaus and Zaichkowsky, 2020). AI technologies, including robotics, not only facilitate human experiences but also support critical business processes, enabling structured automated services and enhanced customer experiences (Lee and Trim, 2022).

The strategic integration of AI in business decision-making processes has proven to be instrumental in enhancing customer experiences. By leveraging AI technologies, businesses can analyze data more effectively, personalize services, and provide real-time solutions, ultimately leading to improved customer satisfaction, loyalty, and competitive advantage in the market.

1.5 Disadvantages of artificial intelligence in decision making

The following are the disadvantages of artificial intelligence in decision making

- lack of transparency and interpretability of AI algorithms
- bias in AI decision-making
- errors or malfunctions in AI systems
- implementation of AI systems in business decision-making can be costly and resource-intensive
- lack of emotions
- security and privacy
- job replacement
- lack of creativity and innovation

Lack of transparency and interpretability of AI algorithms

One of the disadvantages of using artificial intelligence (AI) for decision making in business is the lack of transparency. AI algorithms are increasingly being used to mediate social processes, business transactions, and governmental decisions (Mittelstadt *et al.*, 2016). However, there is often a gap between the design and operation of these algorithms and our understanding of their ethical implications (Mittelstadt *et al.*, 2016). This lack of transparency can have severe consequences for individuals, groups, and societies as a whole (Mittelstadt *et al.*, 2016).

Transparency is important because it allows individuals to understand how decisions are being made and to have recourse against system outcomes (Bell, Nov and Stoyanovich, 2023). Without transparency, individuals may not be able to effectively challenge or question the decisions made by AI systems (Bell, Nov and Stoyanovich, 2023). For example, if someone is rejected for a loan and the reason for that decision is their age, they may not have any recourse to challenge that decision (Bell, Nov and Stoyanovich, 2023).

Furthermore, the lack of transparency in AI decision making can lead to biased or discriminatory results (Soleimani *et al.*, 2021). AI algorithms are often trained on biased datasets, which can perpetuate and amplify existing biases (Soleimani *et al.*, 2021). This can result in unfair and discriminatory outcomes, such as biased hiring practices or discriminatory loan decisions (Soleimani *et al.*, 2021).

To address the lack of transparency in AI decision making, there is a need for regulatory frameworks that require transparency mechanisms (Bell, Nov and Stoyanovich, 2023). These mechanisms should allow individuals to understand how decisions are being made and provide them with recourse against unfair or discriminatory outcomes (Bell, Nov and Stoyanovich, 2023). Additionally, businesses should strive to develop AI systems that are unbiased and transparent in their decision-making processes (Soleimani *et al.*, 2021).

Potential for bias

One of the disadvantages of using artificial intelligence (AI) for decision making in business is the potential for bias. AI algorithms are trained on large datasets, and if these datasets contain biased or discriminatory information, the algorithms can perpetuate and amplify those biases (Caliskan, Bryson and Narayanan, 2017).

Research has shown that machine learning applied to human language can result in human-like biases (Caliskan, Bryson and Narayanan, 2017). These biases can be morally neutral, such as biases towards certain objects or concepts, or they can be problematic biases related to race or gender (Caliskan, Bryson and Narayanan, 2017). For example, if an AI algorithm is trained on a dataset that contains gender biases in career choices, it may perpetuate those biases and lead to discriminatory outcomes in hiring or promotion decisions (Caliskan, Bryson and Narayanan, 2017).

Furthermore, AI algorithms can also reflect and reinforce the status quo distribution of gender with respect to certain domains (Caliskan, Bryson and Narayanan, 2017). This means that if there are existing gender imbalances in certain industries or professions, AI algorithms may continue to perpetuate those imbalances rather than promoting gender equality (Caliskan, Bryson and Narayanan, 2017).

To mitigate bias in AI decision making, it is important to carefully curate and evaluate the training datasets to ensure they are representative and free from biases (Caliskan, Bryson and Narayanan, 2017). Additionally, ongoing monitoring and auditing of AI systems can help identify and address any biases that may emerge during their operation (Özdemir et al., 2021).

Errors or malfunctions can be a significant disadvantage of using artificial intelligence (AI) for decision making in business

Errors or malfunctions can be a significant disadvantage of using artificial intelligence (AI) for decision making in business. As AI systems become more complex and sophisticated, there is an increased risk of unintended and harmful behavior that may arise from poor design or implementation (Amodei *et al.*, 2016). These accidents can have serious consequences for businesses, including financial losses, reputational damage, and legal liabilities.

One of the potential sources of errors or malfunctions in AI systems is the design of the objective function. The objective function defines the goal or task that the AI system is trying to optimize. If the objective function is not properly defined or aligned with the desired outcomes, the AI system may exhibit unintended and harmful behavior (Amodei *et al.*, 2016). For example, if the objective function is solely focused on maximizing profit without considering ethical considerations, the AI system may make decisions that prioritize short-term gains at the expense of long-term sustainability or societal well-being.

Another source of errors or malfunctions is the scalability of supervision. AI systems often require large amounts of labeled data to learn and make accurate predictions. However, obtaining and labeling such data can be time-consuming, expensive, or even infeasible in certain domains (Amodei *et al.*, 2016). As a result, AI systems may not receive sufficient supervision or feedback, leading to suboptimal or erroneous decision making.

Errors or malfunctions can also arise during the learning process of AI systems. Safe exploration is a challenge in AI, as the system needs to explore and learn from its environment without causing harm or unintended consequences (Amodei *et al.*, 2016). Additionally, distributional shift refers to the situation where the data distribution during training differs from the distribution encountered during deployment, leading to performance degradation or unexpected behaviour (Amodei *et al.*, 2016).

To address the issue of errors or malfunctions in AI decision making, research efforts have been focused on AI safety. This includes identifying and addressing specific problems related to accident risk, such as avoiding side effects, avoiding reward hacking, scalable supervision, safe exploration, and distributional shift (Amodei *et al.*, 2016). By understanding these challenges and developing appropriate mitigation strategies, businesses can reduce the likelihood of errors or malfunctions in AI systems.

Errors or malfunctions pose a significant disadvantage of using AI for decision making in business. Poorly designed objective functions, scalability issues in supervision, and challenges during the learning process can lead to unintended and harmful behavior. However, ongoing research in AI safety aims to address these challenges and improve the reliability and robustness of AI systems in decision making.

Implementation challenges can indeed be a disadvantage of using artificial intelligence (AI) for decision making in business

Implementation challenges can indeed be a disadvantage of using artificial intelligence (AI) for decision making in business. The complexity and novelty of AI systems can present challenges during the implementation process, which may hinder their effectiveness and efficiency.

One of the implementation challenges is the need for appropriate infrastructure and technological support. AI systems often require robust computing power, storage capacity, and network infrastructure to operate effectively (Gómez-Caicedo *et al.*, 2022). Without the necessary infrastructure, businesses may struggle to deploy and maintain AI systems, limiting their ability to leverage AI for decision making.

Another implementation challenge is the availability and quality of data. AI systems rely on large amounts of high-quality data to learn and make accurate predictions (Supriyanto, Warsono and Herawati, 2021). However, businesses may face difficulties in accessing relevant data or ensuring its quality, which can impact the performance and reliability of AI systems.

Ethical considerations also play a role in the implementation of AI systems. Businesses need to ensure that AI systems are designed and implemented in a manner that respects privacy, fairness, and transparency (Amodei *et al.*, 2016). This may involve developing and adhering to ethical guidelines, as well as complying with relevant regulations and standards.

To address these implementation challenges, businesses can take several steps.

Firstly, they can invest in the necessary infrastructure and technological capabilities to support AI implementation (Gómez-Caicedo *et al.*, 2022). This may involve upgrading hardware, software, and network infrastructure to ensure optimal performance.

Secondly, businesses should prioritize data management and governance. This includes ensuring data quality, security, and compliance with privacy regulations (Supriyanto, Warsono and Herawati, 2021). Implementing robust data collection, storage, and processing systems can help businesses leverage AI effectively.

Lastly, businesses should establish clear ethical guidelines and frameworks for AI implementation (Amodei *et al.*, 2016). This includes considering the potential biases, fairness, and transparency of AI systems, and ensuring that they align with ethical and legal standards.

The lack of emotions in artificial intelligence (AI) systems can be seen as a disadvantage

The lack of emotions in artificial intelligence (AI) systems can be seen as a disadvantage when it comes to decision making in business. Emotions play a crucial role in human decision making, as they provide valuable information and influence our choices (Istianingsih, Masnun and Pratiwi, 2020). Emotions can help us assess the significance of events, evaluate risks, and consider the impact of our decisions on others (Istianingsih, Masnun and Pratiwi, 2020). However, AI systems lack the ability to experience emotions, which can limit their decision-making capabilities.

Emotional intelligence, which involves the ability to recognize, understand, and manage emotions, is an important aspect of decision making in business (Istianingsih, Masnun and Pratiwi, 2020). Emotional intelligence allows managers to consider the emotional impact of their decisions on employees, stakeholders, and the overall organizational climate (Istianingsih, Masnun and Pratiwi, 2020). It helps in building relationships, resolving conflicts, and making decisions that are sensitive to the needs and well-being of others (Istianingsih, Masnun and Pratiwi, 2020)

Research has shown that emotional intelligence positively influences managerial performance (Istianingsih, Masnun and Pratiwi, 2020). Managers with high emotional intelligence are more likely to make effective decisions, build strong teams, and create a positive work environment (Istianingsih, Masnun and Pratiwi, 2020). On the other hand, the absence of emotions in AI systems can limit their ability to consider the emotional aspects of decision making, potentially leading to suboptimal outcomes.

Security and privacy issues are significant disadvantages of using artificial intelligence (AI) for decision making in business

Security and privacy issues are significant disadvantages of using artificial intelligence (AI) for decision making in business. The following references provide insights into these concerns:

Carlini and Wagner (2017) discusses the vulnerability of neural networks to adversarial examples, which are inputs designed to mislead the AI system. Adversarial attacks can compromise the security of AI systems and lead to incorrect decision making .

Dwork and Roth (2013) introduces the concept of differential privacy, which aims to protect sensitive data while allowing for useful analysis. It highlights the limitations and challenges of achieving privacy in AI systems .

Almpani, Stefaneas and Frangos (2023) emphasize the importance of ethical considerations in AI systems, particularly regarding privacy and social justice. They discuss the need for formal models and frameworks to ensure ethical decision making in AI.

Guo et al. (2023) proposes a privacy-aware intelligent forwarding mechanism for vehicular networks, integrating homomorphic encryption to protect the privacy of information exchanged among vehicles. This highlights the need for privacy-preserving techniques in AI systems .

Overall, these references highlight the need for robust security measures, privacy protection, and ethical considerations in the implementation of AI systems for decision making in business. By addressing these concerns, businesses can mitigate the risks associated with security breaches, privacy violations, and ethical dilemmas in AI decision making.

The use of artificial intelligence (AI) for decision making in business can lead to job replacement, which is considered a disadvantage

The use of artificial intelligence (AI) for decision making in business can lead to job replacement, which is considered a disadvantage. While there are varying perspectives on the extent of job displacement caused by AI, it is acknowledged that automation can substitute for certain tasks while complementing others (Autor, 2015).

The substitution effect of repetitive and easily simulated tasks of AI on jobs can result in structural changes in employment, with routine and mechanical labour being replaced (Zeshuang and Lei, 2022).

Employees' response to job replacement by AI can vary. Some employees may actively update their knowledge and skills to cope with the loss of work resources (Zeshuang and Lei, 2022). The growth need strength of employees plays a role in their ability to adapt to the replacement effect of AI on positions (Zeshuang and Lei, 2022). However, job insecurity and artificial intelligence awareness can lead to work pressure, reduced job-related self-efficacy, and career-related self-management (Zeshuang and Lei, 2022).

It is crucial for businesses to consider the potential impact of job replacement and take measures to mitigate its negative consequences. This may involve providing opportunities for upskilling and reskilling employees to adapt to changing job requirements (Zeshuang and Lei, 2022). Additionally, fostering a supportive organizational culture and addressing job insecurity can help alleviate the negative effects of AI-induced job displacement (Zeshuang and Lei, 2022).

The lack of creativity and innovation

The lack of creativity and innovation can be seen as a potential disadvantage of using artificial intelligence (AI) for decision making in business. While AI systems excel at processing and analyzing large amounts of data, they may struggle to generate truly novel and creative ideas that humans are capable of producing.

AI systems typically rely on existing data and patterns to make decisions, which limits their ability to think outside the box and come up with innovative solutions (Metcalf, Askay and Rosenberg, 2019). They lack the ability to think abstractly, make intuitive leaps, and consider unconventional approaches that humans can bring to the decision-making process (Metcalf et al., 2019).

Creativity and innovation are essential for businesses to stay competitive and adapt to changing market conditions. They enable organizations to develop new products, services, and strategies that can drive growth and success (Bogachov *et al.*, 2020). Human creativity is often fueled by emotions, experiences, and the ability to think beyond logical constraints, which are aspects that AI systems currently lack (Bogachov *et al.*, 2020).

However, it is important to note that AI can still play a role in supporting and enhancing human creativity and innovation. AI systems can assist in data analysis, pattern recognition, and generating insights that can inform human decision making (Bogachov *et al.*, 2020). They can help identify trends, uncover hidden patterns, and provide recommendations that humans can then use as a basis for creative problem-solving and decision making (Bogachov *et al.*, 2020).

To leverage the benefits of AI while addressing the limitations in creativity and innovation, businesses can adopt a collaborative approach that combines human expertise with AI capabilities (Metcalf, Askay and Rosenberg, 2019). By integrating AI systems into multidisciplinary teams, organizations can harness the power of human creativity and critical thinking while leveraging the computational capabilities of AI (Metcalf, Askay and Rosenberg, 2019). This collaborative approach can lead to more innovative and effective decision making in business.

The lack of creativity and innovation is a potential disadvantage of using AI for decision making in business. While AI systems excel at data processing and analysis, they may struggle to generate truly novel and creative ideas. However, by adopting a collaborative approach that combines human creativity with AI capabilities, businesses can leverage the strengths of both to drive innovation and make more effective decisions.

1.6 Various models of IDSS

Expert system based IDSS

Intelligent Decision Support Systems (IDSS) have garnered significant attention across various domains due to their capacity to aid decision-makers in complex problem-solving scenarios by leveraging artificial intelligence technologies (Yang, 2023). These systems are developed to integrate knowledge reasoning, model calculations, and data analysis to offer decision support (Jia *et al.*, 2022). In the realm of medical decision-making, Intelligent Medical Decision Support Systems (IMDSSs) have been created to support clinicians by transforming raw medical data into sophisticated algorithms, thereby facilitating clinical decision-making processes (Aljaaf *et al.*, 2014). The incorporation of artificial intelligence into decision support systems has facilitated the development of proactive systems capable of predicting outcomes, such as the popularity of online news articles (Fernandes, Vinagre and Cortez, 2015).

The evolution of IDSS development has progressed through various stages, from traditional decision support systems to more advanced systems based on artificial intelligence and data warehouses (Jia *et al.*, 2022). These systems are tailored to aid decision-makers by furnishing them with detailed, real-time information to enhance their decision-making processes (Adla, 2007). By amalgamating decision support systems with artificial intelligence technologies, IDSS can assist in resolving intricate decision problems through logical reasoning and analysis (Han, 2017). Furthermore, the exploration of integrating intelligent systems with conventional systems has been undertaken to coordinate multiple agents for diagnostic decisions, emphasizing the potential of expert systems within decision support frameworks (O'Leary and Watkins, 1992).

In the financial sector, IDSS has played a pivotal role in harnessing artificial intelligence for activities such as financial processing and economic management (Zhao and Saeed, 2022b). Decision support systems founded on artificial intelligence have been devised to support senior managers in making optimal decisions by providing intelligent management systems (Zhao, 2022). Additionally, the utilization of deep neural networks and transfer learning h as been suggested for decision support from financial disclosures, showcasing the potential of advanced technologies in enhancing decision-making processes (Kraus and Feuerriegel, 2017).

The architecture of expert systems is crucial in the design and development of IDSS, with methodologies like backward chaining and forward chaining being utilized to enhance system performance (Durgaprasad, Ganesh and Manjunatha, 2021). Evaluation frameworks have also been established to evaluate the effectiveness of intelligent decision support systems, ensuring that these systems meet the required standards and deliver accurate results (Phillips-Wren *et al.*, 2009). Furthermore, the exploration of evolutionary-based optimization techniques has been conducted to enhance the intelligence and adaptability of decision support systems within enterprises (Nikravesh, 2005).

The literature on expert system-based intelligent decision support systems underscores the evolution of these systems from traditional decision support frameworks to advanced AI-driven systems. By integrating artificial intelligence, data analysis, and knowledge reasoning, IDSS have showcased their potential in various domains, including healthcare, finance, and crisis management. The development of proactive systems, integration of intelligent agents, and utilization of deep learning technologies highlight the continuous advancements in the field of intelligent decision support systems.

Machine learning based IDSS

Intelligent Decision Support Systems (IDSS) have seen significant advancements through the integration of machine learning techniques, including supervised, unsupervised, semi-supervised, and reinforcement learning, to enhance decision-making processes across various domains (Jebadurai *et al.*, 2022). Machine learning, a subset of artificial intelligence, enables systems to learn from data and improve their performance over time, thereby empowering decision support systems with the capability to extract insights and patterns from vast datasets (Miklošík *et al.*, 2019). The utilization of supervised machine learning algorithms, such as decision trees, support vector machines, and naive Bayes classifiers, has been instrumental in enhancing predictive modeling for tasks like customer churn prediction and diabetes mellitus forecasting (Khodabandehlou and Rahman, 2017; Ismail and Materwala, 2021). These algorithms aid in the development of accurate models by learning from labeled data and making predictions based on patterns identified during the training phase (Juyal* *et al.*, 2020).

In the context of intelligent decision support systems, the application of unsupervised machine learning techniques has been pivotal in scenarios where labeled data is scarce or unavailable (Herrero, Corchado and Jiménez, 2011). Unsupervised learning algorithms, such as neural models, have been employed for tasks like country and political risk analysis, enabling the extraction of hidden patterns and structures from data without the need for predefined labels (Herrero, Corchado and Jiménez, 2011). These approaches have been instrumental in providing valuable insights for decision-makers in fields like economics and multinational corporations (Herrero, Corchado and Jiménez, 2011). Furthermore, the integration of unsupervised learning methods in decision support systems has facilitated the automatic extraction of rules and identification of patterns from data, contributing to more informed decision-making processes (Herrero, Corchado and Jiménez, 2011).

Semi-supervised machine learning, which combines elements of both supervised and unsupervised learning, has emerged as a valuable approach in enhancing decision support systems (Khonde and Ulagamuthalvi, 2020). By leveraging semi-supervised classifiers in ensemble approaches, systems can effectively detect anomalies and intrusions in distributed systems, thereby bolstering security measures and decision-making capabilities (Khonde and Ulagamuthalvi, 2020). This hybrid architecture enables decision support systems to benefit from the strengths of both supervised and unsupervised learning paradigms, leading to more robust and accurate outcomes in tasks like intrusion detection (Khonde and Ulagamuthalvi, 2020).

Reinforcement learning, another key branch of machine learning, has been increasingly integrated into intelligent decision support systems to enable systems to learn optimal decision-making strategies through interaction with an environment (Zorn *et al.*, 2019). By employing reinforcement learning algorithms, decision support systems can adapt and improve their decision-making processes based on feedback received from the environment, leading to more dynamic and adaptive systems (Zorn *et al.*, 2019). This approach has been particularly valuable in domains like healthcare, where systems need to continuously learn and evolve based on changing conditions and feedback (Silva and Schwamm, 2022).

The integration of machine learning techniques, including supervised, unsupervised, semi-supervised, and reinforcement learning, has significantly enhanced the capabilities of intelligent decision support systems across various domains. By leveraging these diverse approaches, decision support systems can extract valuable insights, make accurate predictions, and adapt to dynamic environments, ultimately empowering decision-makers with the tools needed to navigate complex decision-making scenarios.

Data mining

Data mining techniques are essential for enhancing the capabilities of Intelligent Decision Support Systems (IDSS) by extracting valuable insights from vast datasets. The integration of data mining methods such as association rule learning, classification, clustering, and regression has revolutionized decision-making processes across various domains (Rupnik *et al.*, 2006). Data mining enables the discovery of hidden patterns and relationships within data, facilitating an inductive approach to data analysis and enhancing decision support capabilities (Rupnik *et al.*, 2006).

Association rule learning, a data mining technique, has been instrumental in identifying relationships and patterns in large datasets, enabling decision support systems to make informed decisions based on these associations (Rupnik *et al.*, 2006). By uncovering frequent patterns, association rule learning assists in understanding the dependencies between variables, thereby aiding decision-makers in predicting outcomes and optimizing strategies (Rupnik *et al.*, 2006). This approach has been particularly valuable in domains like retail for market basket analysis and recommendation systems (Rupnik *et al.*, 2006).

Classification, another key data mining technique, plays a vital role in categorizing data into predefined classes or labels, enabling decision support systems to make predictions and decisions based on past observation (Cortez, 2023). By leveraging classification algorithms like decision trees, support vector machines, and neural networks, IDSS can classify data into distinct categories, facilitating tasks such as customer segmentation and risk assessment

(Cortez, 2023). Classification algorithms are essential for building predictive models that assist decision-makers in understanding trends and patterns within datasets (Cortez, 2023).

Clustering, a data mining technique focused on grouping similar data points together, has been widely used in intelligent decision support systems for tasks like customer segmentation and anomaly detection (Aljaaf *et al.*, 2014). By clustering data based on similarities, decision support systems can identify patterns and structures within datasets, enabling decision-makers to gain insights into complex data relationships (Aljaaf *et al.*, 2014). Clustering algorithms like k-means and hierarchical clustering have been instrumental in enhancing decision support capabilities by organizing data into meaningful clusters (Aljaaf *et al.*, 2014).

Regression analysis, a fundamental data mining technique, is employed in intelligent decision support systems to model the relationship between variables and predict continuous outcomes (Kuo, Hong and Huang, 2010). By fitting regression models to data, decision support systems can forecast trends, estimate values, and make informed decisions based on historical data patterns (Kuo, Hong and Huang, 2010). Regression analysis is crucial for tasks like sales forecasting, risk assessment, and resource allocation within decision support systems (Kuo, Hong and Huang, 2010).

The integration of data mining techniques such as association rule learning, classification, clustering, and regression has significantly enhanced the capabilities of Intelligent Decision Support Systems. By leveraging these methods, decision support systems can extract valuable insights, predict outcomes, and optimize decision-making processes across various domains, ultimately empowering decision-makers with the tools needed to navigate complex decision scenarios.

Neural networks

Neural networks have significantly impacted Intelligent Decision Support Systems (IDSS) by enhancing decision-making processes through their ability to learn from data, identify complex patterns, and support informed decision-making based on relationships within datasets (Zhao *et al.*, 2019). The integration of neural network-based techniques in decision support systems has advanced model selection and forecasting tasks, as evidenced by studies demonstrating the efficacy of neural networks in improving predictive modeling and decision outcomes (Zhao *et al.*, 2019). This technological approach has been particularly beneficial in fields requiring accurate forecasting and optimal model selection for improved decision outcomes.

In the healthcare sector, the use of neural network-based decision support systems has notably influenced disease diagnosis and outcome prediction, with research highlighting their role in improving diagnostic accuracy and aiding clinical decision-making processes (Fan *et al.*, 2019). Neural networks have proven effective in processing medical data, recognizing patterns, and assisting healthcare professionals in making well-informed decisions, ultimately contributing to enhanced patient care and treatment outcomes.

Financial decision-making has also seen improvements through the incorporation of neural network-based intelligent systems, particularly in intelligent financial processing. Studies on artificial intelligence-assisted decision support systems based on neural networks have emphasized the efficiency of these systems in refining financial decision-making processes by analyzing financial data, predicting market trends, and optimizing investment strategies (Deng *et al.*, 2023). By utilizing neural networks, financial institutions can make data-driven decisions, manage risks, and seize market opportunities more effectively.

Furthermore, neural networks have been instrumental in enhancing decision support systems in various applications, including anomaly detection, cancer diagnosis, and credit-risk evaluation. Research has shown the effectiveness of neural networks in network anomaly intrusion detection, demonstrating their ability to identify and address security threats efficiently (Huang *et al.*, 2023). Additionally, in cancer diagnosis, neural networks have leveraged demographic data to improve disease diagnosis accuracy, leading to better patient outcomes and treatment strategies (Gao, 2024).

The versatility of neural networks in decision support systems extends to diverse applications such as predicting stock trends, optimizing labor productivity, and early detection of mental health conditions. Studies have highlighted the role of neural networks in stock trend prediction, labor productivity optimization, and early detection of depression, showcasing their utility in guiding investment decisions, enhancing labor efficiency in construction projects, and facilitating mental health assessment and intervention. By harnessing neural networks, decision-makers can gain valuable insights, make informed decisions, and optimize strategies across various domains.

In conclusion, the integration of neural network-based intelligent decision support systems has significantly improved decision-making processes by enabling insights extraction, outcome prediction, and decision strategy optimization within complex and dynamic environments. From healthcare to finance and beyond, neural networks continue to be essential tools for decision-makers navigating intricate datasets, predicting trends, and making informed choices. The ongoing advancements in neural network technologies are poised to reshape the landscape of intelligent decision support systems, providing decision-makers with sophisticated tools for data-driven decision-making and strategic planning.

Decision trees

Decision trees have emerged as a fundamental component in the realm of Intelligent Decision Support Systems (IDSS), offering a structured and intuitive approach to decision-making processes across various domains. The utilization of decision trees in IDSS has been pivotal in enhancing predictive modeling, classification, and pattern recognition tasks, thereby empowering decision-makers with valuable insights and informed strategies (Hamim, Benabbou and Sael, 2021).

The study by Hamim, Benabbou and Sael (2021) introduced an ontology-based decision support system that leveraged the Decision Tree algorithm for model selection and forecasting tasks, showcasing the efficacy of decision trees in enhancing predictive capabilities within decision support systems (Hamim, Benabbou and Sael, 2021). This approach highlights the adaptability of decision trees in accommodating various machine learning models to optimize decision outcomes based on efficiency metrics (Hamim, Benabbou and Sael, 2021).

Decision trees, characterized by internal decision nodes and leaf nodes, have been instrumental in classification tasks within decision support systems. Audemard, Koriche and Marquis (2020) emphasized the finite tree structure of decision trees, where internal nodes represent decision points based on features, and leaf nodes signify outcome labels, underscoring the interpretability and logical flow of decision trees in classification tasks (Audemard, Koriche and Marquis, 2020). This structured representation enables decision-makers to navigate through decision paths and derive actionable insights from complex datasets (Audemard, Koriche and Marquis, 2020).

Moreover, decision trees have been integrated into intelligent support systems for monitoring and machining processes, showcasing their versatility in data mining and decision-making applications. Rojek et al. (2022) highlighted decision trees as basic data mining methods that facilitate knowledge discovery and decision support in monitoring processes, emphasizing their role in uncovering patterns and supporting informed decision-making. This integration underscores the significance of decision trees in extracting actionable insights from data for enhanced decision support (Rojek *et al.*, 2022).

The simplicity and interpretability of decision trees have made them a popular choice for prediction and classification tasks in various domains. (Khan, Saeidlou and Saadat, 2019) emphasized the widespread use of decision tree algorithms in prediction and classification due to their straightforward nature and effectiveness in handling complex decision problems (Khan, Saeidlou and Saadat, 2019). This simplicity, coupled with robust predictive capabilities, positions decision trees as valuable tools for decision support systems across diverse applications (Khan, Saeidlou and Saadat, 2019).

In conclusion, decision trees play a crucial role in the development of Intelligent Decision Support Systems, offering a structured and interpretable framework for decision-making processes. From model selection and forecasting to classification and pattern recognition, decision trees have demonstrated their versatility and effectiveness in empowering decision-makers with valuable insights and informed strategies within complex decision scenarios.

Fuzzy logic

Fuzzy logic-based Intelligent Decision Support Systems (IDSS) have gained prominence for their ability to handle uncertainty and imprecision in decision-making processes across diverse domains. Fuzzy logic offers a flexible and intuitive approach to decision support, enabling systems to model complex relationships and make informed decisions based on vague or incomplete information Akilli et al. (2014).

The study by Akilli et al. (2014) highlighted the application of fuzzy logic in evaluating raw milk quality, emphasizing its role in providing a realistic and objective perspective in decision-making processes. This approach underscores the adaptability of fuzzy logic in handling complex decision scenarios and offering valuable insights for improved decision support (Akilli et al., 2014).

In the financial domain, fuzzy logic has been instrumental in developing multi-agent financial decision support systems. Korczak, Hernes and Bac (2015) emphasized the use of fuzzy logic derived from fuzzy set theory to facilitate approximate reasoning in financial decision-making, showcasing its effectiveness in dealing with uncertainty and imprecise data. This application of fuzzy logic in financial decision support systems highlights its capability to enhance decision-making processes in dynamic and volatile markets.

Moreover, fuzzy logic has been applied in diverse fields such as microbiology and machine monitoring for decision support. (Ertekin and Kaya, 2020) discussed the use of fuzzy logic in determining the microbiological quality of fermented sausage samples, illustrating its simplicity and power in problem-solving and decision-making tasks. Additionally, Kao introduced a fuzzy logic approach assisted by a multiple regression model for in-process machine monitoring systems, demonstrating the effectiveness of fuzzy logic in surface roughness recognition and decision support.

In the healthcare sector, fuzzy logic has been utilized for pediatrics disease diagnosis and therapeutic management. Saleem, Ismaeel and George (2008) presented a fuzzy expert system for pediatrics diseases diagnosis, highlighting fuzzy logic as a branch of artificial intelligence that simulates human reasoning in dealing with uncertain or incomplete data for accurate disease diagnosis. Furthermore, Othman and Zeki (2023) discussed the therapeutic management of diseases, focusing on hypertriglyceridemia, and emphasized the efficiency of fuzzy logic in converting complex decision trees into intelligent procedures for effective disease management.

Fuzzy logic-based Intelligent Decision Support Systems have proven to be valuable tools for handling uncertainty and imprecision in decision-making processes. From evaluating milk quality to financial decision support and disease diagnosis, fuzzy logic offers a robust framework for modeling complex relationships and providing informed decision support across various domains.

Case based reasoning

Case-Based Reasoning (CBR) has emerged as a powerful technique in the development of Intelligent Decision Support Systems (IDSS), offering a unique approach to decision-making processes by leveraging past experiences and cases to provide informed recommendations and solutions. The application of CBR in various domains has showcased its effectiveness in handling complex decision scenarios and supporting decision-makers with valuable insights (Montani and Jain, 2013).

In the medical field, CBR has been utilized for disease diagnosis and therapeutic management. Ehtesham et al. (2019) developed an intelligent system for the diagnosis of oral medicine using a CBR approach, highlighting the three-stage process of collecting clinical data, constructing a cases database, and implementing the CBR cycle for accurate diagnosis and decision support (Ehtesham *et al.*, 2019). This application of CBR underscores its role in leveraging past cases to provide tailored solutions in medical decision-making processes.

Furthermore, CBR has been instrumental in developing decision support systems for specific medical conditions such as breast cancer. Sekar et al. (2018) explored the use of CBR in breast cancer management, emphasizing the integration of explicit domain knowledge ontology to enhance decision support capabilities for healthcare professionals (Sekar *et al*., 2018). This application of CBR in disease management showcases its potential in providing personalized and effective solutions based on historical cases and domain knowledge.

In the field of odontology, CBR has been applied for retreatment predictions, demonstrating its utility in practical decision-making scenarios. (Campo *et al.*, 2016) presented a CBR-based decision support system designed to predict the feasibility of performing retreatments in odontology, highlighting the effectiveness of CBR in providing recommendations based on similar past cases (Campo *et al*., 2016). This application of CBR underscores its role in supporting practical decision-making processes in specialized domains.

Moreover, CBR has been integrated into various decision support systems for forecasting, supplier selection, and e-maintenance. Pedro and Burstein (2003) proposed a multi-stage framework that integrates CBR and fuzzy multicriteria decision-making techniques for intelligent decision support, showcasing the versatility of CBR in handling complex decision scenarios (Pedro and Burstein, 2003). Additionally, Yu, Iung and Panetto (2003) integrated CBR into an e-maintenance system to enhance autonomous decision-making abilities and problem-solving processes, highlighting the effectiveness of CBR in improving system performance and convergence time (Yu, Iung and Panetto, 2003).

Case-Based Reasoning has proven to be a valuable methodology in the development of Intelligent Decision Support Systems, offering a unique approach to decision-making by leveraging past cases and experiences. From disease diagnosis to supplier selection and maintenance systems, CBR provides decision-makers with tailored recommendations and solutions based on historical cases and domain knowledge, ultimately enhancing decision support capabilities across diverse domains.

Bayesian networks

Bayesian Networks (BNs) have emerged as a powerful tool in the development of Intelligent Decision Support Systems (IDSS), offering a probabilistic framework for modeling complex relationships and making informed decisions based on uncertainty and incomplete information. The application of BNs in decision support systems has showcased their effectiveness in handling diverse decision scenarios and providing valuable insights for decision-makers (Saraiva *et al.,* 2020).

In the medical domain, BNs have been utilized for disease diagnosis and treatment management. For instance, developed a clinical decision support system based on a BN model to assess the need for orthodontic treatment in patients, highlighting the ability of BNs to provide personalized recommendations based on probabilistic reasoning and domain knowledge (Thanathornwong, 2018). This application underscores the role of BNs in enhancing medical decision-making processes by incorporating uncertainty and probabilistic reasoning.

Moreover, BNs have found applications in various fields such as public health systems and natural hazard warnings. presented a trust-based mechanism for automatic decision-making in public health systems, leveraging BNs to provide probabilistic reasoning and decision support in dynamic contexts (Teles *et al.*, 2014). Additionally, discussed the use of BNs for issuing natural hazard warnings, emphasizing the potential of BNs to incorporate decision and utility nodes for optimizing warning systems and minimizing risks (Economou *et al.*, 2016).

In the context of transportation and activity pattern decisions, BNs have been integrated into decision-making models to improve performance and accuracy. focused on enhancing the performance of a multiagent rule-based model for activity pattern decisions by incorporating BN properties to capture interdependencies among variables and optimize decision processes (Janssens *et al.*, 2004). This application highlights the versatility of BNs in modeling complex decision scenarios and improving decision outcomes.

Furthermore, BNs have been applied in the context of software measurement programs and object recognition. introduced a BN-based method to analyze the validity of data in software measurement programs, showcasing the benefits of BNs in handling small and incomplete datasets and providing decision support based on probabilistic reasoning (Saraiva *et al*., 2020). Additionally, discussed the applications of BNs in Artificial Intelligence for object recognition tasks, emphasizing their role in capturing causal relationships and uncertainty for effective decision-making (Buuren, Klerk and Veldkamp, 2017).

Bayesian Networks have proven to be valuable tools in the development of Intelligent Decision Support Systems, offering a probabilistic framework for modeling uncertainty and making informed decisions. From disease diagnosis to natural hazard warnings and transportation decisions, BNs provide decision-makers with probabilistic reasoning and personalized recommendations, ultimately enhancing decision support capabilities across diverse domains.

Multi criteria decision analysis

Multicriteria Decision Analysis (MCDA) has become a vital methodology in the development of Intelligent Decision Support Systems (IDSS), offering a structured approach to decision-making processes when multiple objectives need to be considered. The application of MCDA in various domains has demonstrated its effectiveness in handling complex decision scenarios and providing decision-makers with valuable insights for informed decision-making (Franco and Montibeller, 2011).

In the realm of software systems, introduced a generalized multicriteria decision support system, MKO-2, designed to model and solve linear and linear integer multicriteria optimization problems (Vassileva *et al.*, 2007). This system showcases the versatility of MCDA in addressing optimization challenges and providing decision support based on multiple criteria, thereby enhancing the decision-making process in software engineering contexts.

Moreover, MCDA has found applications in diverse fields such as health care, transportation, and energy management. emphasized the importance of structured, explicit approaches to decision-making in health care using MCDA techniques to improve the quality of decision-making processes (Thokala *et al.*, 2016). Additionally, developed a GIS-based MCDA system for organic waste management, demonstrating the utility of MCDA in spatial decision-making processes (Yalçinkaya and Kirtiloğlu, 2019).

In the context of energy management, proposed an MCDA framework for the optimal location and dimensioning of capacitors in microgrids, highlighting the use of MCDA algorithms to analyze decision variables and objective functions in energy distribution systems (Águila *et al.*, 2021). This application underscores the role of MCDA in optimizing energy systems and minimizing costs through informed decision-making processes.

Furthermore, MCDA has been integrated into decision support systems for job satisfaction evaluation, information systems project selection, and psychological disorders diagnosis. developed a decision support system based on genetic algorithms and the Multi-Criteria Satisfaction Analysis (MUSA) method for measuring job satisfaction, showcasing the application of MCDA in evaluating subjective criteria (Aouadni and Rebaï, 2016). Additionally, focused on multicriteria group decision support for information systems project selection, emphasizing the role of MCDA in selecting optimal projects based on multiple criteria (Yeh *et al.*, 2009).

In conclusion, Multicriteria Decision Analysis plays a crucial role in the development of Intelligent Decision Support Systems, offering a structured approach to decision-making processes when multiple objectives need to be considered. From software systems optimization to health care and energy management, MCDA provides decision-makers with a systematic framework for evaluating alternatives, optimizing outcomes, and making informed decisions across diverse domains.

1.7 Technology-Organisation-Environment by Small and Medium Enterprises

Complexity as a Technological Factor in the Adoption of Recent Technology by SMEs

The adoption of recent technology by small and medium-sized enterprises (SMEs) is influenced by various technological factors within the Technology-Organization-Environment (TOE) framework. This critical analysis will examine the role of complexity as a technological factor in the adoption of recent technology by SMEs using the TOE framework, based on the selected references from the past five years.

Kruse et al. (2014) presents a conceptual model for the adoption of health information technology (HIT) based on a systematic review. The study identifies complexity as one of the factors associated with the adoption of HIT. Complexity refers to the perceived difficulty or intricacy of implementing and using the technology. The research suggests that the complexity of the technology can influence the adoption decisions of SMEs. Higher complexity may pose challenges for SMEs with limited resources and technical expertise, potentially hindering the adoption of recent technologies (Kruse et al., 2014).

Rahman et al. (2020) explores the adoption of social media by SMEs and its impact on financial sustainability. Although the main focus is on social media adoption, the authors discuss the concept of technological competence, which can be related to complexity. Technological competence refers to the internal IT infrastructure and existing IT skills within the organization. SMEs with higher technological competence are more likely to adopt new technologies, suggesting that they may be better equipped to handle the complexity associated with the adoption process (Rahman *et al.*, 2020).

Bride, Abraham and Roman (2011) examines the organizational factors associated with the use of contingency management in substance abuse treatment centers. Although the main focus is on the healthcare sector, the study provides insights into the adoption of treatment innovations and the role of organizational factors. Complexity is identified as a factor that differs between the adoption of psychosocial interventions and pharmacological innovations. The complexity of the technology or intervention can influence the adoption decisions of organizations, including SMEs ((Bride, Abraham and Roman, 2011).

Fuller, Hardin and Scott (2007) discusses the diffusion of virtual innovation and the factors that influence an organization's willingness to adopt new technology. Complexity is recognized as one of the three most important factors at the organizational level. It refers to the perceived difficulty or intricacy of the technology. The research suggests that higher complexity can act as a barrier to technology adoption, as organizations may perceive it as challenging to implement and use (Fuller, Hardin and Scott, 2007).

Compatibility as a Technological Factor in the Adoption of Recent Technology by SMEs

The adoption of recent technology by small and medium-sized enterprises (SMEs) is influenced by various technological factors within the Technology-Organization-Environment (TOE) framework. This critical analysis will examine the role of compatibility as a technological factor in the adoption of recent technology by SMEs using the TOE framework, based on the selected references from the past five years.

Qalati et al. (2022) focuses on the adoption of social media by SMEs and its impact on performance. The study identifies compatibility as one of the technological factors that influence social media adoption. Compatibility refers to the extent to which the technology aligns with the existing systems, processes, and practices of the organization. The research findings reveal that compatibility has a significant effect on social media adoption by SMEs. When the technology is perceived as compatible with the organization's operations, it is more likely to be adopted (Qalati *et al.*, 2022).

Kumar Bhardwaj, Garg and Gajpal (2021) investigates the determinants of blockchain technology adoption in supply chains by SMEs in India. The study highlights the role of compatibility as a technological factor in the adoption of blockchain technology. Compatibility refers to the fit between the technology and the existing systems and processes of the organization. The research findings indicate that technology compatibility has a positive influence on the intention of SMEs to adopt blockchain technology. When the technology is perceived as compatible with the organization's supply chain operations, SMEs are more likely to adopt it (Kumar Bhardwaj, Garg and Gajpal, 2021).

Chong and Olesen (2017) provides a meta-analysis of eco-effectiveness from a technology-organization-environment perspective. The study discusses the determinants of organizational innovation adoption, including technological factors. Compatibility is identified as one of the technological factors associated with innovation adoption. It refers to the fit between the innovation and the existing technological capabilities and systems of the organization. The research suggests that compatibility plays a role in influencing the adoption of eco-effective practices by organizations (Chong and Olesen, 2017).

Vuononvirta et al. (2011) explores the compatibility of telehealth with healthcare delivery. Although the main focus is on telehealth, the study provides insights into the role of compatibility as a technological factor. Compatibility is identified as having three aspects: individual, process, and organizational compatibility. Individual compatibility refers to the fit between the technology and the individual users, process compatibility refers to the fit between the technology and the existing processes, and organizational compatibility refers to the fit between the technology and the overall organizational context. The research emphasizes the importance of compatibility in facilitating the adoption and integration of telehealth into healthcare delivery (Vuononvirta *et al.*, 2011).

In conclusion, compatibility is a significant technological factor in the adoption of recent technology by SMEs. The selected references highlight the influence of compatibility on technology adoption decisions, particularly in relation to the fit between the technology and the existing systems, processes, and practices of the organization. Understanding and addressing compatibility are crucial for SMEs to effectively adopt and leverage new technologies.

Relative Advantage as a Technological Factor in the Adoption of Recent Technology by SMEs

The adoption of recent technology by small and medium-sized enterprises (SMEs) is influenced by various technological factors within the Technology-Organization-Environment (TOE) framework. This critical analysis will examine the role of relative advantage as a technological factor in the adoption of recent technology by SMEs using the TOE framework, based on the selected references from the past five years.

C. Lin and Ho (2010) focuses on the determinants of green practice adoption for logistics companies in China. While the primary focus is on green practices, the study highlights the importance of relative advantage as a technological factor. Relative advantage refers to the perceived superiority of the new technology over existing alternatives. The research findings suggest that the economic and financial advantages associated with green practices influence the adoption decisions of logistics companies. When the new technology offers clear advantages in terms of environmental and financial performance, SMEs are more likely to adopt it (C. Y. Lin and Ho, 2010).

Chong and Olesen (2017) provides a meta-analysis of eco-effectiveness from a technology-organization-environment perspective. The study discusses the determinants of organizational innovation adoption, including technological factors. Relative advantage is identified as one of the technological factors associated with innovation adoption. It refers to the perceived benefits and strengths of the new technology compared to existing alternatives. The research findings indicate that relative advantage plays a significant role in influencing the adoption of eco-effective practices by organizations (Chong and Olesen, 2017).

Khalid et al. (2021) examines the adoption of renewable energy by consumers. The study emphasizes the importance of relative advantage as a technological factor in the adoption of renewable energy technology. Relative advantage refers to the benefits and strengths of renewable energy compared to conventional energy sources. The research findings suggest that awareness of the relative advantages of renewable energy is crucial for promoting its adoption by households. When the benefits and strengths of renewable energy are well understood, households are more likely to adopt it (Khalid *et al.*, 2021).

Kotu et al. (2022) investigates the potential impact of groundnut production technology on the welfare of smallholder farmers in Ghana. The study utilizes the TOE framework to predict the adoption of the new groundnut technology. Relative advantage is identified as one of the overarching factors that affect adoption decisions in agriculture. The research suggests that the perceived relative advantage of the new technology influences the adoption decisions of smallholder farmers. When the new technology offers clear advantages in terms of productivity and income generation, farmers are more likely to adopt it (Kotu *et al.*, 2022).

Shatta et al., (2020) explores the influence of relative advantage on e-procurement adoption in developing countries, specifically in the context of Tanzania. The study highlights the direct and indirect influences of relative advantage on e-procurement adoption. Relative advantage refers to the perceived benefits and advantages of e-procurement compared to traditional procurement methods. The research findings suggest that relative advantage plays a significant role in influencing the adoption of e-procurement in the public sector. When the benefits and advantages of e-procurement are recognized, organizations are more likely to adopt it (Shatta *et al.*, 2020).

Relative advantage is a significant technological factor in the adoption of recent technology by SMEs. The selected references highlight the influence of relative advantage on technology adoption decisions, particularly in relation to the perceived benefits and strengths of the new technology compared to existing alternatives. Understanding and promoting the relative advantages of new technologies are crucial for SMEs to effectively adopt and leverage them.

Top Management Support as an Organizational Factor in the Adoption of Recent Technology by SMEs

The adoption of recent technology by small and medium-sized enterprises (SMEs) is influenced by various organizational factors within the Technology-Organization-Environment (TOE) framework. This critical analysis will examine the role of top management support as an organizational factor in the adoption of recent technology by SMEs using the TOE framework, based on the selected references from the past five years.

Duan, Deng and Corbitt (2012) focuses on the adoption of e-market by Australian SMEs and highlights the importance of top management support. The study identifies top management support as a critical determinant for adopting e-market in SMEs. Top management support creates a supportive climate and provides adequate resources for technology adoption, helping to overcome barriers and resistance to change within the organization. The research findings suggest that top management support plays a crucial role in facilitating the adoption of new technologies by SMEs (Duan et al., 2012).

Nair, Chellasamy and Singh (2019) investigates the readiness factors for information technology (IT) adoption in SMEs, specifically in an Indian context. The study emphasizes the influence of top management support within the organizational context. Top management support is identified as a factor that affects IT adoption readiness in SMEs. The research highlights the importance of top management support in creating a supportive climate and providing resources for technology adoption, contributing to the readiness of SMEs to adopt new technologies (Nair, Chellasamy and Singh, 2019).

Eze et al. (2019) explores the adoption of mobile marketing technology in service SMEs. The study presents a multi-perspective framework for understanding the factors influencing the adoption of mobile marketing devices. Top management support is recognized as a critical factor that influences the adoption of mobile marketing technology. The research findings suggest that top management support plays a significant role in creating awareness among staff and justifying the adoption of new technologies in SMEs (Eze *et al.*, 2019).

Rahman et al. (2020) examines the adoption of social media by SMEs and its impact on financial sustainability. The study emphasizes the role of top management support in the adoption of social media. Top management support is identified as a factor that positively affects a firm's propensity to adopt social media. The research findings suggest that the attitude of owners/managers and their support for new technologies influence the adoption decisions of SMEs (Rahman *et al.*, 2020).

Hoque et al. (2016) investigates the adoption of information and communication technology (ICT) for development. The study highlights the barriers to ICT adoption in SMEs, including the lack of top management support. The research findings suggest that top management support is crucial for overcoming barriers and facilitating the adoption of ICT in SMEs. Lack of awareness and understanding of the benefits of ICT, along with inadequate resources, can be addressed through top management support (Hoque *et al.*, 2016).

Top management support is an organizational factor that plays a significant role in the adoption of recent technology by SMEs. The selected references highlight the importance of top management support in creating a supportive climate, providing resources, and overcoming barriers to technology adoption. Understanding and promoting top management support are crucial for SMEs to effectively adopt and leverage new technologies.

Technology readiness as an Organizational Factor in the Adoption of Recent Technology by SMEs

In the realm of small and medium-sized enterprises (SMEs), the adoption of recent technologies is a critical factor that can significantly impact their performance and competitiveness in the market. One of the key determinants influencing this adoption is the concept of technology readiness as an organizational factor. Technology readiness refers to the preparedness of an organization to embrace and effectively utilize new technologies (Hasani *et al.*, 2023). This readiness encompasses various dimensions, including technological, organizational, environmental, and managerial factors (Hasani *et al.*, 2023). Understanding and addressing these dimensions are crucial for SMEs aiming to successfully integrate recent technologies into their operations.

Research by Ghobakhloo et al. (2022) emphasizes the importance of considering technological, organizational, and environmental determinants when examining the adoption of Industry 4.0 technologies by SMEs (Ghobakhloo *et al.*, 2022a). The study underscores the need for SMEs to comprehensively assess factors that may influence their readiness to adopt new technologies, such as Industry 4.0 innovations. By delving into these determinants, SMEs can gain insights into how to navigate the challenges and leverage the opportunities presented by technological advancements.

Moreover, the study by (Maroufkhani, Iranmanesh and Ghobakhloo, 2022) sheds light on the critical role of organizational readiness in the adoption of big data analytics (BDA) by SMEs (Maroufkhani, Iranmanesh and Ghobakhloo, 2022). Organizational readiness, in this context, encompasses aspects such as financial resources, IT infrastructure, analytics capabilities, skilled human capital, and knowledge resources (Maroufkhani, Iranmanesh and Ghobakhloo, 2022). This highlights the multifaceted nature of readiness that SMEs need to cultivate to effectively implement and benefit from advanced technologies like BDA.

In the context of social media adoption by SMEs, (Qalati *et al.*, 2022) identify various technological, organizational, and environmental factors that influence this process (Qalati *et al.*, 2022).
Factors such as relative advantage, cost-effectiveness, compatibility, entrepreneurial orientation, and customer pressure play significant roles in shaping SMEs' decisions to adopt social media platforms (Qalati *et al.*, 2022). Understanding these factors is crucial for SMEs

seeking to enhance their online presence and engage with customers effectively through social media channels.

Furthermore, the study by (Kumar Bhardwaj, Garg and Gajpal, 2021) delves into the determinants of blockchain technology adoption in supply chains by SMEs in India (Kumar Bhardwaj, Garg and Gajpal, 2021). The research highlights the positive influence of factors like relative advantage, technology compatibility, technology readiness, top management support, perceived usefulness, and vendor support on SMEs' intention to adopt blockchain technology (Kumar Bhardwaj, Garg and Gajpal, 2021). These findings underscore the importance of considering a range of readiness factors when exploring the adoption of specific technologies within SME contexts.

Firm Characteristics as an Organizational Factor in the Adoption of Recent Technology by SMEs

The adoption of recent technology by small and medium-sized enterprises (SMEs) is influenced by various organizational factors within the Technology-Organization-Environment (TOE) framework. This critical analysis will examine the role of firm characteristics as an organizational factor in the adoption of recent technology by SMEs using the TOE framework, based on the selected references from the past five years.

Ghobakhloo et al. (2022b) provide a systematic review of the drivers and barriers of Industry 4.0 technology adoption among manufacturing SMEs. The study highlights the importance of firm characteristics, such as human resources, firm size, and communication structure, in the adoption of Industry 4.0 technologies. The research findings suggest that the particularities of firm characteristics can impact the successful adoption and utilization of advanced technologies by SMEs.

Salim, Business Batu Pahat Johor Malaysia and Jaffar (2020) review cloud-based ERP systems in SMEs and identify firm qualities as a key theme influencing technology adoption. The study emphasizes the importance of firm characteristics, internal pressure, and external pressure in the adoption of cloud-based ERP systems. The research findings suggest that firm qualities, such as organizational readiness and internal and external pressures, play a significant role in shaping the adoption of ERP systems in SMEs.

Yan et al. (2022) explore the implementation strategies for high-performance healthcare simulation centers in China and highlight the role of organizational characteristics in IT implementation performance. The study emphasizes that technology attributes, individual characteristics, and organizational characteristics predict IT implementation performance. The research findings suggest that firm characteristics, such as technology attributes and individual characteristics, influence the successful implementation of IT in organizations.

Pathak, Ashok and Tan (2021) discuss value co-creation in the B2B context and present a conceptual framework for understanding the implications of firm characteristics. The study utilizes the TOE model and focuses on the elements of the firm, including technology, organization, and environment. The research findings suggest that firm characteristics, such as organizational size, attitudes towards innovation, and learning culture, influence the adoption of technology and value co-creation in SMEs.

Zahra, Dhewanto and Utama (2021) examine the adoption of emerging technology in the fashion industry and highlight the significance of firm characteristics. The study identifies strategic roadmap and perceived value of emerging technologies as critical determinants of adoption. The research findings suggest that firm characteristics, such as strategic planning and perceived value, play a crucial role in driving the adoption of emerging technologies in SMEs.

In conclusion, firm characteristics are essential organizational factors that can influence the adoption of recent technology by SMEs. The selected references highlight the importance of human resources, firm size, communication structure, organizational readiness, and internal and external pressures in shaping technology adoption decisions. Understanding and leveraging firm characteristics are crucial for SMEs to effectively adopt and leverage new technologies within their organizations.

Government Policies as an Environmental Factor in the Adoption of Recent Technology by SMEs

The adoption of recent technology by small and medium-sized enterprises (SMEs) is influenced by various environmental factors within the Technology-Organization-Environment (TOE) framework. This critical analysis will examine the role of government policies as an environmental factor in the adoption of recent technology by SMEs using the TOE framework, based on the selected references from the past five years.

Rahayu and Day (2015) focuses on the adoption of e-commerce by SMEs in Indonesia. The study explores the determinant factors of e-commerce adoption and highlights the influence of government policies. Government policies, such as financial support, resources, and tax relief, are identified as factors that motivate SMEs to adopt e-commerce technology. The research findings suggest that government policies play a significant role in creating an enabling environment for technology adoption by SMEs (Rahayu and Day, 2015).

Effendi, Sugandini and Istanto (2020) investigates the adoption of social media by SMEs, with a specific focus on the impact of COVID-19. The study utilizes the TOE model and examines the effects of technological, organizational, and environmental factors on social media adoption. The research findings suggest that government regulations can motivate SMEs to adopt social media technology. Government support, such as financial assistance and resources, can influence SMEs' decision to adopt social media platforms (Effendi et al., 2020).

Qalati et al. (2022) explores the effects of technological, organizational, and environmental factors on the adoption of social media by SMEs. The study utilizes path analysis and examines the influence of various factors, including government policies. The research findings suggest that government policies, such as regulations and incentives, can have a significant impact on social media adoption by SMEs. The study highlights the importance of government support in creating a favorable environment for technology adoption (Qalati *et al.*, 2022).

Bakar et al. (2020) investigates the adoption of sustainable technology in Malaysian SMEs. The study examines the role of government policies in influencing the adoption of sustainable technology. The research findings suggest that government policies can play a crucial role in encouraging SMEs to adopt sustainable technology. By introducing policies that promote sustainability and provide incentives, the government can influence SMEs' attitudes and encourage the adoption of sustainable technology(Bakar *et al.,* 2020).

Stakeholder Influence as an Environmental Factor in the Adoption of Recent Technology by SMEs

The adoption of recent technology by small and medium-sized enterprises (SMEs) is influenced by various environmental factors within the Technology-Organization-Environment (TOE) framework. This critical analysis will examine the role of stakeholder influence as an environmental factor in the adoption of recent technology by SMEs using the TOE framework, based on the selected references from the past five years.

Camilleri (2019) focuses on the technology acceptance of digital media for stakeholder engagement by SMEs. The study explores the factors influencing SMEs' adoption of digital media for stakeholder engagement and highlights the role of stakeholder influence. Stakeholder influence refers to the impact and involvement of external stakeholders, such as customers, suppliers, and the community, in shaping the adoption decisions of SMEs. The research findings suggest that stakeholder influence plays a significant role in motivating SMEs to adopt digital media for stakeholder engagement. The expectations and demands of stakeholders can drive SMEs to embrace new technologies to enhance their communication and engagement efforts (Camilleri, 2019).

Apulu, Latham and Moreton (2011) investigates the factors affecting the effective utilization and adoption of sophisticated ICT solutions by SMEs. The study examines the role of stakeholder influence in the adoption of ICT solutions. Stakeholder influence refers to the impact and involvement of external stakeholders, such as customers, suppliers, and industry associations, in shaping the adoption decisions of SMEs. The research findings suggest that stakeholder influence can play a significant role in motivating SMEs to adopt sophisticated ICT solutions. The expectations and requirements of stakeholders can drive SMEs to embrace advanced technologies to meet their needs and remain competitive (Apulu, Latham and Moreton, 2011).

Li et al. (2019) explores the critical challenges for Building Information Modeling (BIM) adoption in small and medium-sized enterprises (SMEs) in China. The study examines the role of stakeholder influence in BIM adoption. Stakeholder influence refers to the impact and involvement of external stakeholders, such as clients, contractors, and regulatory bodies, in shaping the adoption decisions of SMEs. The research findings suggest that stakeholder influence can present challenges for BIM adoption in SMEs. The expectations and requirements of stakeholders, along with the interconnections between stakeholders, can influence the adoption decisions and implementation of BIM in SMEs (Li *et al.*, 2019).

Bellantuono, Pontrandolfo and Scozzi (2016) focuses on capturing the stakeholders' view in sustainability reporting. The study emphasizes the importance of stakeholder influence in shaping sustainability reporting practices. Stakeholder influence refers to the impact and involvement of external stakeholders, such as investors, customers, and NGOs, in shaping the reporting decisions of SMEs. The research findings suggest that stakeholder influence can drive SMEs to adopt sustainable reporting practices. The expectations and demands of stakeholders for transparency and accountability can influence SMEs to adopt and improve their sustainability reporting practices (Bellantuono, Pontrandolfo and Scozzi, 2016).

Rahman et al. (2020) investigates the adoption of social media by SMEs and its impact on financial sustainability. The study examines the role of stakeholder influence in the adoption of social media. Stakeholder influence refers to the impact and involvement of external stakeholders, such as customers, competitors, and industry associations, in shaping the adoption decisions of SMEs. The research findings suggest that stakeholder influence positively impacts the adoption of social media by SMEs. The expectations and pressures from stakeholders, along with the potential benefits of social media, can motivate SMEs to adopt and leverage social media platforms (Rahman *et al.*, 2020).

In conclusion, stakeholder influence is an environmental factor that can influence the adoption of recent technology by SMEs. The selected references highlight the importance of stakeholder expectations, demands, and pressures in shaping the adoption decisions of SMEs. Understanding and responding to stakeholder influence are crucial for SMEs to effectively adopt and leverage new technologies.

Competitive Pressure as an Environmental Factor in the Adoption of Recent Technology by SMEs

The adoption of recent technology by small and medium-sized enterprises (SMEs) is influenced by various environmental factors within the Technology-Organization-Environment (TOE) framework. This critical analysis will examine the role of competitive pressure as an environmental factor in the adoption of recent technology by SMEs using the TOE framework, based on the selected references from the past five years.

Hamad, Elbeltagi and El-Gohary (2018) focuses on the adoption of business-to-business e-commerce by Egyptian manufacturing SMEs and its impact on competitive advantage. The study explores the factors influencing e-commerce adoption and highlights the role of competitive pressure. Competitive pressure refers to the influence and competition faced by SMEs from other firms in the industry. The research findings suggest that competitive pressure has a significant positive effect on the adoption of e-commerce by SMEs. The need to remain competitive and gain an advantage in the market drives SMEs to adopt e-commerce technology (Hamad, Elbeltagi and El-Gohary, 2018).

Higón (2011) investigates the impact of information and communication technologies (ICT) on innovation activities in UK SMEs. The study examines the role of competitive pressure in driving ICT adoption and innovation. Competitive pressure refers to the pressure faced by SMEs to stay competitive and innovative in the market. The research findings suggest that competitive pressure can drive SMEs to adopt ICT solutions and engage in innovation activities. The need to keep up with competitors and gain a competitive edge motivates SMEs to embrace new technologies (Higón, 2011).

Ali Abbasi et al. (2022) explores the determinants of SMEs' adoption of social media marketing and the moderating role of competitive industry. The study examines the influence of competitive pressure on the adoption of social media marketing. Competitive pressure refers to the pressure faced by SMEs from competitors in the industry. The research findings suggest that competitive pressure can moderate the relationship between determinants and the adoption of social media marketing. When SMEs face intense competition, they are more likely to adopt social media marketing to stay competitive and reach their target audience (Ali Abbasi *et al.*, 2022).

Apulu, Latham and Moreton (2011) considers the factors affecting the effective utilization and adoption of sophisticated ICT solutions in Nigerian SMEs. The study examines the role of competitive pressure in driving the adoption of advanced ICT solutions. Competitive pressure refers to the pressure faced by SMEs to stay competitive and utilize advanced technologies. The research findings suggest that competitive pressure can influence SMEs to adopt sophisticated ICT solutions. The need to remain competitive and improve efficiency drives SMEs to embrace advanced technologies (Apulu, Latham and Moreton, 2011).

Supplier Efficacy as an Environmental Factor in the Adoption of recent Technology by SMEs

The adoption of recent technology by small and medium-sized enterprises (SMEs) is influenced by various environmental factors within the Technology-Organization-Environment (TOE) framework. This critical analysis will examine the role of supplier efficacy as an environmental factor in the adoption of recent technology by SMEs using the TOE framework, based on the selected references from the past five years.

Wuttke, Rosenzweig and Heese (2019) investigates the adoption of supply chain finance (SCF) by SMEs. The study examines the factors influencing SCF adoption, including supplier efficacy. Supplier efficacy refers to the ability of suppliers to access financing and reduce financing costs. The research findings suggest that suppliers with limited access to financing tend to adopt SCF faster, indicating that supplier efficacy plays a role in driving the adoption of financial technologies by SMEs (Wuttke, Rosenzweig and Heese, 2019).

Chowdhury, Lau and Pittayachawan (2019) explores the operational supply risk mitigation of SMEs and its impact on operational performance. The study examines the role of buyer-supplier social capital in mitigating operational supply risk. Supplier efficacy, in terms of buyer-supplier social capital, refers to the strength of the relationship and collaboration between buyers and suppliers. The research findings suggest that buyer-supplier social capital can help mitigate operational supply risk, leading to improved operational performance for SMEs (Chowdhury, Lau and Pittayachawan, 2019).

Kumar Bhardwaj, Garg and Gajpal (2021) investigates the determinants of blockchain technology adoption in supply chains by SMEs in India. The study examines the factors influencing the adoption of blockchain technology, including supplier efficacy. Supplier efficacy refers to the ability of suppliers to adopt and utilize blockchain technology in their supply chains. The research findings suggest that supplier efficacy, along with other factors such as knowledge bases and power relationships, can influence the adoption of blockchain technology by SMEs (Kumar Bhardwaj, Garg and Gajpal, 2021).

Liu, Zhang and Ye (2019) explores the adoption of sustainable practices from a supplier's perspective. The study examines the factors influencing the adoption of sustainable practices, including supplier efficacy. Supplier efficacy refers to the knowledge bases and power relationships of suppliers in adopting sustainable practices. The research findings suggest that supplier efficacy plays a critical role in the adoption of sustainable practices by SMEs. Suppliers with strong knowledge bases and power relationships are more likely to adopt and implement sustainable practices (Liu, Zhang and Ye, 2019).

1.8 Summary

The Technology-Organization-Environment (TOE) framework is a widely used model for understanding the factors influencing the adoption of technology innovation in organizations. It considers three key factors: technology, organization, and environment. The TOE framework focuses on three subheadings: complexity, compatibility, relative advantage, and organization. Complexity refers to the difficulty in understanding and using a technology, compatibility refers to the extent to which a technology aligns with an organization's existing systems, processes, and values, and relative advantage refers to the perceived benefits of adopting a technology compared to existing alternatives. Organization refers to the size and scale of an organization, technological readiness, and top management support. Environment refers to competitive pressure, stakeholder influence, supplier efficacy, and government support. The TOE framework provides a comprehensive model for understanding the factors influencing technology adoption in organizations, exploring subheadings such as complexity, compatibility, trialability, relative advantage, observability, firm size, employee cooperation, top management support, competitive pressure, stakeholder influence, supplier efficacy, and government support. Despite some criticisms regarding the framework's explanatory power, it remains a widely used and valuable tool for analyzing technology adoption.

Decision support systems (DSS) have evolved to provide intelligent assistance to decision-makers by incorporating artificial intelligence tools and technologies such as knowledge bases, natural language, genetic algorithms, multi-agent systems, fuzzy logic, and neural networks. These systems are used to formulate, model, analyze, and interpret problem results. A Decision Support System consists of three essential parts: database management subsystems, model management subsystems, and user interface subsystems.

In an Intelligent DSS, a Knowledge Management Subsystem is included, which involves categorizing, analyzing, and synthesizing information. This process requires human involvement, as technology cannot produce knowledge. Internal and external sources of information and knowledge can be categorized as internal and external.

SMEs play a crucial role in the Indian economy, contributing significantly to employment generation, exports, and GDP. The growth and development of SMEs in India are influenced by factors such as the implementation of a green organizational culture, formalization of human resource management practices, access to finance, and succession planning.

Green practices can enhance competitiveness and sustainability, but resource constraints and limited awareness among SME owners/managers pose challenges. Improving formalization of human resource management can enhance productivity and performance. Access to affordable credit and financial services is also critical for SMEs' growth and development.

Furthermore, SMEs in India face challenges related to succession planning and business continuity, as lack of proper succession planning can lead to disruptions in business operations. Developing effective succession planning strategies can ensure the continuity and long-term sustainability of SMEs.

Artificial intelligence (AI) has the potential to replace human intelligence in various aspects of life, including service industries, business decision-making, and human resources. AI can automate tasks, replace portfolio managers, and replace customer service representatives. However, AI cannot replace human care, thinking, and interaction.

Artificial intelligence (AI) has revolutionized business decision-making by offering real-time advantages over human processes. Decision Support Systems (DSS), Business Intelligence (BI), and AI enhance the decision-making process by providing valuable insights and analysis. AI enables access to vast amounts of data and facilitates real-time analysis in the cloud, providing instantaneous information support for managerial decisions. The potential of AI to revolutionize decision-making is highlighted by studies on Business Intelligence Approach based on Deep Learning (2023) and Hamad et al. (2020). AI's capabilities include reasoning, problem-solving, object recognition, word recognition, and decision-making. By harnessing AI technologies, businesses can gain a competitive edge by making data-driven decisions in real-time, leveraging the speed and accuracy of AI.

Artificial intelligence (AI) has revolutionized business decision-making by offering real-time advantages over human processes. Decision Support Systems (DSS), Business Intelligence (BI), and AI are instrumental in enhancing the decision-making process by providing valuable insights and analysis. AI enables access to vast amounts of data and facilitates real-time analysis in the cloud, offering instantaneous information support for managerial decisions. The potential of AI to revolutionize business decision-making is highlighted by the survey on Business Intelligence Approach based on Deep Learning (2023). AI systems can continuously learn and adapt based on new information, enabling businesses to make agile decisions in dynamic environments.

The real-time advantage of AI over humans in business decision-making lies in its ability to swiftly process and analyze massive volumes of data, identify patterns, and generate insights at a pace that surpasses human cognitive capabilities. AI systems can continuously learn and adapt based on new information, enabling businesses to make agile decisions in dynamic environments.

Predictive capabilities of AI extend beyond healthcare, with studies exploring the use of predictive techniques in optimizing food and bioresources transformation processes. However, it is important to consider the limitations and ethical implications of AI-driven decision-making. Overall, AI's potential to revolutionize various aspects of life, including business, requires further exploration and understanding of its dynamics and potential impacts.

Artificial intelligence (AI) offers numerous advantages in decision-making processes, including automation, competitive edge, sustainability, research and development, personalized recommendation, continuous learning, lack of bias, scalability, enhanced customer experience, and resource allocation. Automation in decision-making can streamline processes, increase efficiency, and reduce the potential for human error. However, it also introduces challenges related to human-AI interaction, bias mitigation, and ethical considerations.

AI and fuzzy logic tools can be universally applied to support decision-making under uncertainty in various business environments. By utilizing AI, businesses can make objective and well-grounded decisions, taking into account environmental factors and minimizing the impact of uncertainty.

A competitive edge is provided by AI through its ability to analyze large amounts of data quickly and accurately, enabling businesses to make more informed decisions based on comprehensive and objective analyses of data. AI can also enhance decision-making in human resources (HR), ensuring companies have the right talent in place to drive their competitive advantage.

In addition to automation, AI can mediate the relationship between AI and competitive advantage by effectively integrating AI into IT infrastructure. This integration allows businesses to leverage AI across various functions, such as supply chain management, customer relationship management, and decision support systems, to enhance overall performance and competitiveness.

Research and development (R&D) is another significant advantage of AI in business, as it can support and enhance the R&D process, leading to improved innovation, efficiency, and competitiveness. AI technologies can analyze vast amounts of data and generate personalized recommendations tailored to individual preferences and needs, enhancing customer experiences, increasing satisfaction, and driving business growth.

Artificial intelligence (AI) has several advantages in decision-making in business. It can analyze customer demographics, behaviors, and interactions to generate personalized recommendations for optimal actions. AI systems can continuously learn and improve their performance over time, allowing businesses to adapt to changing environments and stay ahead of the competition. One key aspect of continuous learning in AI is reinforcement learning, which allows AI systems to learn from interactions with the environment and receive feedback in the form of rewards or penalties. This iterative process can also address the challenge of forgetting previous knowledge when learning new tasks.

AI systems have the potential to reduce bias and promote fairness in decision-making processes. By recognizing and addressing biases in AI systems, businesses can take steps to mitigate them and ensure fair decision-making processes. Ethical decision-making in AI systems is crucial, considering societal and moral norms, transparency, and safety.

Artificial intelligence (AI) has become a crucial tool in modern business operations, offering numerous benefits. One of the key advantages of utilizing AI in decision-making processes is the enhancement of scalability, which is essential for businesses to adapt to changing market dynamics, customer demands, and operational requirements. The integration of AI technologies, particularly machine learning (ML), plays a significant role in enhancing a company's scalability and improving overall operations. AI-driven decision-making can have far-reaching implications for various business models, facilitating growth and sustainability in competitive markets. The concept of being "AI First" for enterprises has revolutionized traditional business practices and opened new avenues for optimizing decision-making processes and operational efficiency.

In the realm of decision-making frameworks, AI-driven approaches prioritize business strategy as a fundamental driver, ensuring that AI is utilized to address pertinent business challenges, fostering innovation and competitive advantage. By integrating AI decision-making frameworks that are aligned with business objectives, companies can maximize the value derived from AI technologies, further enhancing their scalability and operational effectiveness.

Enhancing customer experience is another advantage of AI in business. AI technologies can analyze customer data, preferences, and behaviors to provide personalized and tailored experiences, leading to improved customer satisfaction and loyalty.

Artificial intelligence (AI) has several disadvantages in decision making, including lack of transparency and interpretability of AI algorithms, potential bias, errors or malfunctions in AI systems, implementation costs, emotional loss, security and privacy concerns, job replacement, and lack of creativity and innovation.

Transparency is crucial as it allows individuals to understand how decisions are being made and have recourse against system outcomes. AI algorithms are often trained on biased datasets, which can perpetuate and amplify existing biases, leading to unfair outcomes. To address this issue, regulatory frameworks that require transparency mechanisms should be implemented, and businesses should strive to develop AI systems that are unbiased and transparent in their decision-making processes.

Bias is another significant disadvantage of AI in decision making. As AI systems become more complex and sophisticated, there is an increased risk of unintended and harmful behavior that may arise from poor design or implementation. This can have serious consequences for businesses, including financial losses, reputational damage, and legal liabilities.

One potential source of errors or malfunctions in AI systems is the design of the objective function, which defines the goal or task the AI system is trying to optimize. If the objective function is not properly defined or aligned with the desired outcomes, the AI system may exhibit unintended and harmful behavior. Another source of errors or malfunctions is the scalability of supervision, which can lead to suboptimal or erroneous decision making.

To address these issues, research efforts have focused on AI safety, which includes identifying and addressing specific problems related to accident risk, such as avoiding side effects, reward hacking, scalable supervision, safe exploration, and distributional shift. By understanding these challenges and developing appropriate mitigation strategies, businesses can reduce the likelihood of errors or malfunctions in AI systems.

Implementation challenges in AI for decision making in business can be a disadvantage due to the complexity and novelty of AI systems. These challenges include the need for appropriate infrastructure and technological support, the availability and quality of data, and ethical considerations. To address these challenges, businesses can invest in necessary infrastructure, prioritize data management and governance, and establish clear ethical guidelines and frameworks.

Emotional intelligence, which involves the ability to recognize, understand, and manage emotions, is an important aspect of decision making in business. However, AI systems lack the ability to experience emotions, which can limit their decision-making capabilities. Emotional intelligence positively influences managerial performance, but the absence of emotions in AI systems can limit their ability to consider the emotional impact of decisions.

Security and privacy issues are significant disadvantages of using AI for decision making in business. Adversarial attacks can compromise the security of AI systems, and differential privacy can protect sensitive data while allowing for useful analysis. Ethical considerations in AI systems, particularly regarding privacy and social justice, need formal models and frameworks.

Robust security measures, privacy protection, and ethical considerations are essential in the implementation of AI systems for decision making in business. By addressing these concerns, businesses can mitigate risks associated with security breaches, privacy violations, and ethical dilemmas in AI decision making.

Artificial intelligence (AI) in business decision-making can lead to job replacement, a disadvantage. AI can replace repetitive tasks and replace routine labor, causing structural changes in employment. Employees' responses to AI job replacement can vary, with some adapting to the loss of resources and others experiencing job insecurity. To mitigate these negative consequences, businesses should provide opportunities for upskilling and reskilling employees, foster a supportive organizational culture, and address job insecurity.

Creativity and innovation are also potential disadvantages of AI in business. AI systems may struggle to generate novel ideas, as they rely on existing data and patterns. However, AI can support and enhance human creativity and innovation by assisting in data analysis, pattern recognition, and generating insights.

To leverage AI's benefits while addressing limitations in creativity and innovation, businesses can adopt a collaborative approach that combines human expertise with AI capabilities. This approach can harness the power of human creativity and critical thinking while leveraging AI's computational capabilities. This approach can lead to more innovative and effective decision-making in business.

Intelligent Decision Support Systems (IDSS) are a growing field that leverages artificial intelligence technologies to aid decision-makers in complex problem-solving scenarios. These systems integrate knowledge reasoning, model calculations, and data analysis to offer decision support. They have evolved from traditional decision support frameworks to more advanced systems based on AI and data warehouses.

In the medical sector, IDSSs have been developed to support clinicians by transforming raw medical data into sophisticated algorithms, facilitating clinical decision-making processes. The integration of AI into IDSS has also led to the development of proactive systems capable of predicting outcomes.

In the financial sector, IDSS has played a pivotal role in harnessing artificial intelligence for activities such as financial processing and economic management. Deep neural networks and transfer learning have been suggested for decision support from financial disclosures.

The architecture of expert systems is crucial in the design and development of IDSS, with methodologies like backward chaining and forward chaining being utilized to enhance system performance. Evaluation frameworks have been established to ensure the effectiveness of IDSS systems, and evolutionary-based optimization techniques have been explored to enhance the intelligence and adaptability of decision support systems within enterprises.

The integration of machine learning techniques, including supervised, unsupervised, semi-supervised, and reinforcement learning, has significantly enhanced the capabilities of IDSS across various domains. By leveraging these diverse approaches, decision support systems can extract valuable insights, make accurate predictions, and adapt to dynamic environments, ultimately empowering decision-makers with the tools needed to navigate complex decision-making scenarios.

Data mining techniques, such as association rule learning, classification, clustering, and regression, have significantly improved the capabilities of Intelligent Decision Support Systems (IDSS) by extracting valuable insights from vast datasets. These techniques enable the discovery of hidden patterns and relationships within data, facilitating an inductive approach to data analysis and enhancing decision support capabilities.

Association rule learning helps identify relationships and patterns in large datasets, enabling decision support systems to make informed decisions based on these associations. Classification algorithms like decision trees, support vector machines, and neural networks help IDSS categorize data into distinct categories, facilitating tasks such as customer segmentation and risk assessment. Clustering, a data mining technique focused on grouping similar data points together, helps identify patterns and structures within datasets, enabling decision-makers to gain insights into complex data relationships.

Regression analysis is crucial for tasks like sales forecasting, risk assessment, and resource allocation within IDSS. By fitting regression models to data, decision support systems can forecast trends, estimate values, and make informed decisions based on historical data patterns.

Neural networks, a subset of artificial intelligence, have played a crucial role in improving decision support systems by enabling them to learn from data, identify patterns, and make informed decisions based on complex relationships within datasets. They have been employed in various applications, including disease diagnosis, financial decision-making, anomaly detection, cancer diagnosis, and credit-risk evaluation.

In conclusion, the integration of neural network-based intelligent decision support systems has significantly improved decision-making processes across various domains, empowering decision-makers with sophisticated tools for informed and data-driven decision-making.

Decision trees and fuzzy logic are two key components in Intelligent Decision Support Systems (IDSS). Decision trees offer a structured and intuitive approach to decision-making processes, enhancing predictive modeling, classification, and pattern recognition tasks. They have been integrated into intelligent support systems for monitoring and machining processes, showcasing their versatility in data mining and decision-making applications.

Fuzzy logic, on the other hand, offers a flexible and intuitive approach to decision support, enabling systems to model complex relationships and make informed decisions based on vague or incomplete information. It has been applied in various fields, such as evaluating raw milk quality, developing multi-agent financial decision support systems, and determining the microbiological quality of fermented sausage samples. In the healthcare sector, fuzzy logic has been used for pediatrics disease diagnosis and therapeutic management.

Case-based reasoning is another key component of IDSS, enabling decision-makers to make informed decisions based on the complexity of the situation. It has been used in various fields, such as healthcare, to simulate human reasoning in dealing with uncertain or incomplete data. In conclusion, decision trees and fuzzy logic are essential tools for handling uncertainty and imprecision in decision-making processes, providing valuable insights and informed strategies for decision-makers in various domains.

Case-Based Reasoning (CBR) is a powerful technique in the development of Intelligent Decision Support Systems (IDSS), leveraging past experiences and cases to provide informed recommendations and solutions. It has been used in various domains, including medical, odontology, forecasting, supplier selection, and e-maintenance. CBR has been used for disease diagnosis, therapeutic management, breast cancer management, and retreatment predictions. It has also been integrated into decision support systems for forecasting, supplier selection, and e-maintenance.

Bayesian Networks (BNs) are a probabilistic framework for modeling complex relationships and making informed decisions based on uncertainty and incomplete information. They have been used in the medical domain for disease diagnosis and treatment management, public health systems, natural hazard warnings, transportation and activity pattern decisions, software measurement programs, and object recognition. BNs have been integrated into decision-making models to improve performance and accuracy, and have been applied in software measurement programs and object recognition tasks.

In conclusion, Bayesian Networks have proven to be valuable tools in the development of IDSS, offering a probabilistic framework for modeling uncertainty and making informed decisions. They provide decision-makers with probabilistic reasoning and personalized recommendations, enhancing decision support capabilities across diverse domains.

Multicriteria Decision Analysis (MCDA) is a crucial methodology in Intelligent Decision Support Systems (IDSS), offering a structured approach to decision-making when multiple objectives need to be considered. It has been applied in various domains, such as software systems, health care, transportation, energy management, job satisfaction evaluation, information systems project selection, and psychological disorders diagnosis. MCDA has been used to model and solve linear and linear integer multicriteria optimization problems, enhance decision-making in software engineering, and optimize energy systems in microgrids. It has also been integrated into decision support systems for job satisfaction evaluation, information systems project selection, and psychological disorders diagnosis. Overall, MCDA provides a systematic framework for evaluating alternatives, optimizing outcomes, and making informed decisions across diverse domains.

The adoption of recent technology by small and medium-sized enterprises (SMEs) is influenced by various technological factors within the Technology-Organization-Environment (TOE) framework. Complexity, a perceived difficulty or intricacy of implementing and using the technology, can influence SMEs' adoption decisions. Higher complexity may pose challenges for SMEs with limited resources and technical expertise, potentially hindering the adoption of recent technologies.

Technological competence, which refers to the internal IT infrastructure and existing IT skills within the organization, can be related to complexity. SMEs with higher technological competence are more likely to adopt new technologies, suggesting they may be better equipped to handle the complexity associated with the adoption process.

Compatibility is another significant factor in the adoption of recent technology by SMEs. It refers to the extent to which the technology aligns with the existing systems, processes, and practices of the organization. Research findings reveal that compatibility has a significant effect on social media adoption by SMEs. When the technology is perceived as compatible with the organization's operations, it is more likely to be adopted.

Compatibility plays a role in the adoption of blockchain technology in supply chains by SMEs in India. When the technology is perceived as compatible with the organization's supply chain operations, SMEs are more likely to adopt it. Compatibility also influences the adoption of eco-effective practices by organizations.

In conclusion, compatibility is a significant technological factor in the adoption of recent technology by SMEs. Understanding and addressing compatibility are crucial for SMEs to effectively adopt and leverage new technologies.

Relative advantage is a significant factor in the adoption of recent technology by small and medium-sized enterprises (SMEs). It refers to the perceived superiority of new technology over existing alternatives, which can influence the adoption decisions of logistics companies, eco-effectiveness, renewable energy adoption, groundnut production technology, e-procurement adoption, and top management support.

Relative advantage plays a crucial role in promoting the adoption of new technologies by SMEs. Research has shown that when the economic and financial advantages associated with green practices are well understood, SMEs are more likely to adopt them. Additionally, top management support is essential for creating a supportive climate and providing adequate resources for technology adoption, helping to overcome barriers and resistance to change within the organization.

In the context of information technology (IT) adoption, top management support is identified as a factor that affects IT adoption readiness in SMEs. Research has shown that top management support creates a supportive climate and provides adequate resources for technology adoption, contributing to the readiness of SMEs to adopt new technologies.

In the adoption of social media by SMEs, top management support positively affects a firm's propensity to adopt social media. The attitude of owners/managers and their support for new technologies influence the adoption decisions of SMEs.

Top management support is an organizational factor that plays a significant role in the adoption of recent technology by SMEs. Understanding and promoting top management support are crucial for SMEs to effectively adopt and leverage new technologies.

Technology readiness is a critical factor in the adoption of recent technologies by small and medium-sized enterprises (SMEs). This readiness encompasses various dimensions, including technological, organizational, environmental, and managerial factors. Understanding and addressing these dimensions is crucial for SMEs to successfully integrate new technologies into their operations. Research by Ghobakhloo et al. (2022) emphasizes the importance of considering technological, organizational, and environmental determinants when examining the adoption of Industry 4.0 technologies by SMEs.

Maroufkhani, Iranmanesh, and Ghobakhloo (2022) shed light on the critical role of organizational readiness in the adoption of big data analytics (BDA) by SMEs. Qalati et al. (2022) identify various technological, organizational, and environmental factors that influence the process of adopting social media by SMEs. Kumar Bhardwaj, Garg, and Gajpal (2021) delves into the determinants of blockchain technology adoption in supply chains by SMEs in India.

Government policies also play a significant role in the adoption of recent technology by SMEs. Rahayu and Day (2015) explore the determinant factors of e-commerce adoption and highlight the influence of government policies, such as financial support, resources, and tax relief. Effendi, Sugandini, and Istanto (2020) investigate the adoption of social media by SMEs, with a focus on the impact of COVID-19. Qalati et al. (2022) explore the effects of technological, organizational, and environmental factors on the adoption of social media by SMEs, with the importance of government support in creating a favorable environment for technology adoption.

This critical analysis examines the role of stakeholder influence in the adoption of recent technology by small and medium-sized enterprises (SMEs) using the Technology-Organization-Environment (TOE) framework. The study focuses on the factors influencing

SMEs' adoption of digital media for stakeholder engagement, the impact of external stakeholders, such as customers, suppliers, and the community, in shaping their adoption decisions. Stakeholder influence plays a significant role in motivating SMEs to adopt digital media for stakeholder engagement, as the expectations and demands of stakeholders can drive them to embrace new technologies to enhance their communication and engagement efforts.

The study also explores the critical challenges for Building Information Modeling (BIM) adoption in SMEs in China, highlighting the importance of stakeholder influence in shaping adoption decisions. Stakeholder influence can drive SMEs to adopt sustainable reporting practices, as the expectations and demands of stakeholders for transparency and accountability can influence SMEs to adopt and improve their sustainability reporting practices.

Lastly, the study investigates the adoption of social media by SMEs and its impact on financial sustainability. The research findings suggest that stakeholder influence positively impacts the adoption of social media by SMEs, as the expectations and pressures from stakeholders, along with the potential benefits of social media, can motivate SMEs to adopt and leverage social media platforms.

The impact of competitive pressure on the adoption of information and communication technologies (ICT) in UK SMEs is a topic of interest. Competitive pressure can drive SMEs to adopt ICT solutions and engage in innovation activities, as it helps them stay competitive and gain a competitive edge. SMEs also face intense competition, which can moderate the adoption of social media marketing. In Nigeria, the need to remain competitive and improve efficiency drives SMEs to embrace advanced technologies.

Supplier efficacy is another environmental factor influencing the adoption of recent technology by SMEs. Suppliers with limited access to financing tend to adopt SCF faster, indicating that supplier efficacy plays a role in driving the adoption of financial technologies. Buyer-supplier social capital can help mitigate operational supply risk, leading to improved operational performance for SMEs.

Blockchain technology adoption in supply chains by SMEs in India is also influenced by supplier efficacy, along with other factors such as knowledge bases and power relationships. Suppliers with strong knowledge bases and power relationships are more likely to adopt and implement sustainable practices. Overall, competitive pressure and supplier efficacy play crucial roles in the adoption of new technologies and practices by SMEs.

CHAPTER III:
Methodology

3.1 Overview of the research problem

The integration of Intelligent Decision Support Systems (IDSS) in organizational settings is a promising avenue for enhancing decision-making processes. However, there exists a significant gap in understanding the factors influencing the adoption of IDSS within organizations. This gap is underscored by the challenges posed by the complexity and volume of data in modern enterprises, where a large portion of acquired data remains unutilized (Zhu and Kraemer, 2005). The exponential growth of data further emphasizes the need for effective data analytics strategies to support decision-making (Zhu, Kraemer and Xu, 2006). Human decision-making processes are also influenced by cognitive biases and heuristics, leading to potential errors and suboptimal choices (Dwivedi *et al.*, 2021). Cognitive phenomena like hindsight bias and overconfidence compound these challenges, highlighting the importance of IDSS in mitigating human fallibility (Dwivedi *et al.*, 2021).

Despite the evident benefits of IDSS, their adoption within organizational contexts remains underexplored (Zhu and Kraemer, 2005). Understanding the determinants that drive the adoption of IDSS is crucial for maximizing their efficacy and organizational impact. By addressing this gap in the literature, researchers can identify and analyze the factors influencing the adoption of IDSS in organizational decision-making processes (Zhu and Kraemer, 2005). This research aims to provide valuable insights for practitioners, policymakers, and researchers to facilitate the broader integration and utilization of IDSS, ultimately enhancing decision-making effectiveness and organizational performance.

3.2 Operationalisation of theoretical constructs

The Technology-Organization-Environment (TOE) framework is a valuable theoretical model for understanding the adoption and implementation of technology within organizations. This framework suggests that technology adoption is influenced by factors related to the technology itself (T), the organization adopting it (O), and the external environment in which the organization operates (E). Operationalizing the constructs within the TOE framework involves translating these factors into measurable variables or indicators that can be empirically assessed.

Numerous studies have utilized the TOE framework to investigate technology adoption in various contexts. For example, (Alshamaileh, Papagiannidis and Li, 2013) applied the TOE framework to study cloud computing adoption by SMEs in the north east of England, emphasizing the importance of considering technological, organizational, and environmental factors in adoption processes (Alshamaileh, Papagiannidis and Li, 2013). Similarly, (Ghobakhloo, Arias-Aranda and Benitez-Amado, 2011) suggested that the TOE framework is suitable for studying e-commerce adoption in SMEs, highlighting the relevance of understanding the interplay between technology, organization, and environment (Ghobakhloo, Arias-Aranda and Benitez-Amado, 2011).

Furthermore, the TOE framework has been extended and adapted in different studies to explore technology adoption in diverse settings. (Effendi, Sugandini and Istanto, 2020) proposed a TOE model to examine social media adoption in SMEs impacted by COVID-19, showcasing the framework's versatility in addressing contemporary challenges (Effendi, Sugandini and Istanto, 2020). Additionally, (Awa, Ojiabo and Emecheta, 2015) integrated the TOE framework with other theoretical models to enhance the understanding of e-commerce adoption by SMEs, demonstrating the framework's adaptability and integrative nature (Awa, Ojiabo and Emecheta, 2015).

In conclusion, the TOE framework offers a comprehensive perspective for researchers to analyze the complex interplay of technological, organizational, and environmental factors influencing technology adoption within organizations. By operationalizing the constructs within this framework, researchers can gain valuable insights into the drivers and barriers of technology adoption, ultimately contributing to informed decision-making and successful implementation strategies.

3.3 Research design

Quantitative methods of data collection are essential in research, providing structured and numerical insights that can be statistically analyzed to draw meaningful conclusions. The process of using quantitative methods involves collecting data that can be quantified and measured, allowing researchers to analyze relationships, patterns, and trends within the data. This essay delves into the operationalization of quantitative data collection methods, drawing insights from various scholarly references.

The Technology-Organization-Environment (TOE) framework, a widely used theoretical model for understanding technology adoption within organizations, emphasizes the importance of quantitative data collection to assess factors influencing technology adoption (Johnson and Onwuegbuzie, 2004). Quantitative methods enable researchers to measure variables related to technology, organizational characteristics, and external environmental factors, providing a systematic approach to understanding the adoption process.

Studies such as those by (Bourenkov and Popov, 2005) highlight the significance of quantitative approaches in data collection strategies, emphasizing the use of quantitative methods for optimum data-collection planning. Quantitative data collection methods allow researchers to plan and execute data collection processes efficiently, ensuring that data is collected in a systematic and structured manner to facilitate analysis and interpretation.

In the realm of education research, demonstrate the utility of quantitative data collection in analyzing the digital citizenship of social studies teachers, showcasing how quantitative data is collected and analyzed before qualitative data to provide a comprehensive understanding of the research topic (Aygün and İlhan, 2020). This sequential approach to data collection underscores the importance of quantitative methods in establishing a foundation for further qualitative exploration.

Moreover, the integration of quantitative data collection within mixed methods research designs, as discussed by (Fetters, Curry and Creswell, 2013), is essential for investigating complex phenomena in fields such as health services research. By combining quantitative and qualitative data, researchers can gain a holistic understanding of multifaceted processes, enhancing the depth and breadth of their analyses.

Quantitative data collection methods are also instrumental in exploring various research domains, as evidenced by studies such as (Jensenius, 2014) in political science, which emphasizes the significance of fieldwork for collecting quantitative data and addressing challenges encountered during data collection in the field. The use of quantitative methods in fieldwork underscores the importance of rigorous data collection practices to ensure the reliability and validity of research findings.

In conclusion, the operationalization of quantitative data collection methods is essential for conducting rigorous and systematic research across diverse disciplines. By employing quantitative approaches, researchers can gather numerical data, analyze patterns and trends, and derive evidence-based conclusions, thereby advancing knowledge and contributing to evidence-informed decision-making processes.

3.4 Population and sample

Population

The number of Small and Medium Enterprises (SMEs) registered in India is a significant indicator of the country's economic landscape. According to a study by , the Indian Micro, Small, and Medium Enterprises (MSME) sector comprises around 26 million firms, employing approximately 60 million individuals (Batra *et al.*, 2017). These enterprises represent about 80% of the total firms in India and contribute about 8% to the Indian GDP. Additionally, mention that in India, about 95% of the enterprises are SMEs (Mouli and Mahanty, 2017). This highlights the substantial presence and impact of SMEs in the Indian business environment.

Furthermore, the development of the MSME sector in India is crucial for economic growth and employment generation, as emphasized by (Socrates and B. V Gopalakrishna, 2020). The sector plays a vital role in promoting inclusive growth and leveraging India's demographic dividend. Additionally, the study by underscores that SMEs are a dynamic engine of growth in India, contributing significantly to eradicating unemployment, poverty, income inequality, and regional imbalances (Kumar Bhardwaj, Garg and Gajpal, 2021).

In conclusion, the number of SMEs registered in India is substantial, with millions of enterprises operating across various sectors and significantly contributing to the country's economy in terms of GDP, employment generation, and overall growth.

Sample

A diverse sample was selected by utilizing appropriate sampling techniques, considering industry sectors, organizational sizes, and geographical regions across India. The participants had varied experience, educational backgrounds, and gender. Small and medium-sized enterprises from manufacturing, trading, and service sectors were included. The sample was initially drawn from known circles, and then the snowballing effect was adopted to interview more participants.

Data was collected from a sample of 508 participants across India. The sampling size was termed as purposive sampling as it was not an accurate representation of the population.

3.5 Participant selection

Random sampling is a fundamental method in research to ensure the representativeness of a sample from a larger population, aiming to minimize bias and enhance the generalizability of findings. This technique involves selecting individuals from a population in a manner where each member has an equal chance of being chosen, thus reducing the risk of skewed results (Elben *et al*., 2020). The process of random sampling begins with defining the population of interest, which could be any group sharing common characteristics for which conclusions are sought (Elben *et al*., 2020). Subsequently, a sampling frame is created, serving as a reference for sample selection, ensuring it accurately represents the population without any duplications or omissions (Elben *et al*., 2020).

Various methods of random sampling exist, such as simple random sampling, stratified random sampling, and cluster sampling, with the choice depending on factors like research objectives and available resources (Elben *et al*., 2020). In simple random sampling, each population member is assigned a unique identifier, and a subset is randomly chosen to form the sample, ensuring randomness in the selection process (Elben *et al*., 2020). The randomness is crucial to provide every individual an equal opportunity for selection, thus avoiding biases that could skew the results (Elben *et al*., 2020). Determining the appropriate sample size is also essential, considering factors like confidence level and variability within the population to ensure the study's reliability and validity (Elben *et al*., 2020).

Once the random sampling technique and sample size are established, the sample is drawn from the sampling frame using specified methods to maintain randomness (Elben *et al*., 2020). Following data collection, researchers analyze the sample to draw conclusions about the population, often employing statistical techniques for inference (Elben *et al*., 2020). The findings from the sample are then interpreted in the context of the larger population, considering study limitations like sampling error to make inferences about population parameters (Elben *et al*., 2020). The ultimate goal of random sampling is to generalize findings from the sample to the entire population, emphasizing the importance of a representative sample and rigorous sampling processes (Elben *et al*., 2020).

Random sampling is a systematic and unbiased approach to selecting a sample from a population, ensuring each member has an equal chance of inclusion, thereby enhancing the reliability and validity of study findings (Elben *et al*., 2020). By adhering to principles of randomness and employing appropriate sampling techniques, researchers can increase the robustness of their research outcomes and make more accurate inferences about the broader population (Elben *et al*., 2020).

3.6 Instrumentation

In the research, a survey-based instrument method was employed as the primary approach for data collection. This method involved the utilization of a questionnaire as the research instrument. The questionnaire was carefully designed to gather relevant data pertaining to the research objectives. It consisted of a series of structured questions aimed at eliciting specific information from the participants.

Through the survey-based instrument method, researchers sought to systematically gather data from a targeted sample of individuals. The questionnaire was administered to the participants either through online platforms, face-to-face interviews, or other appropriate means depending on the nature of the study and the characteristics of the target population.

The questionnaire design process ensured that the questions were clear, concise, and aligned with the research objectives. Additionally, efforts were made to minimize bias and ensure the validity and reliability of the data collected through the instrument.

Overall, the survey-based instrument method with a questionnaire provided a structured and systematic approach to collecting data, allowing researchers to effectively address their research questions and objectives.

3.7 Data collection procedures

In this research study, the data collection procedure involved a multi-faceted approach, combining simple random sampling, online and offline methods, a network of networks, and snowball sampling techniques.

1. Simple Random Sampling:

The first step in the data collection process was the selection of participants through simple random sampling. This method ensured that every individual in the target population had an equal chance of being selected for the study. Using a random number generator or a similar technique, participants were selected without any bias, providing a representative sample for the research.

2. Online and Offline Methods:

To reach a diverse range of participants, both online and offline data collection methods were employed. Online methods included distributing electronic surveys via email, social media platforms, and online forums. Offline methods involved face-to-face interviews, paper-based surveys distributed in public places, and mailed surveys to individuals without internet access. This hybrid approach ensured inclusivity and broadened the reach of the study across different demographics.

3. Network of Networks:

The data collection process also leveraged a network of networks approach, tapping into existing social networks and organizations to access potential participants. By collaborating with community groups, professional associations, and academic institutions, researchers were able to gain access to individuals who might not have been reached through traditional recruitment methods. This approach facilitated the recruitment of participants with diverse backgrounds and perspectives, enriching the dataset.

4. Snowball Sampling:

In addition to simple random sampling, snowball sampling was utilized to further expand the participant pool. This technique involved recruiting initial participants who then referred other eligible individuals from their social or professional circles to participate in the study. As the process continued, the participant network grew organically, allowing researchers to access hard-to-reach populations and uncover hidden connections within the community.

By employing a combination of simple random sampling, online and offline methods, a network of networks, and snowball sampling, the data collection procedure ensured the inclusion of a diverse range of participants and perspectives. This comprehensive approach enhanced the validity and reliability of the research findings, providing valuable insights into the research topic.

3.8 Data analysis

Structural Equation Modeling (SEM) is a statistical technique that allows researchers to explore and validate complex relationships among variables by analyzing both observed and latent variables (HairJr. *et al.*, 2021). In data analysis, SEM provides a comprehensive approach to understanding the underlying structures within the data by examining direct and indirect effects among variables (Rappaport, Amstadter and Neale, 2019). The process of utilizing SEM involves several key steps that contribute to a thorough analysis of the relationships among variables.

The first step in employing SEM is model specification, where researchers outline a theoretical model illustrating the proposed relationships among the variables of interest (Bentler and Bonett, 1980). This theoretical model serves as a framework for testing hypotheses and understanding the complex interplay of factors influencing the outcome being studied. Subsequently, the measurement model estimation stage involves evaluating the relationships between observed variables and their corresponding latent constructs to ensure that the observed variables effectively capture the underlying constructs they are intended to measure (Bolló *et al.*, 2018).

Once the measurement model is established, researchers proceed to the structural model estimation, where they examine the relationships between latent variables and test the specified paths or hypotheses within the theoretical model (Rappaport, Amstadter and Neale, 2019). This step allows for a deeper exploration of the direct and indirect effects among variables, providing valuable insights into the underlying mechanisms driving the observed associations. Following the structural model estimation, researchers assess the fit of the model to the data using various fit indices such as the Comparative Fit Index (CFI) and the Root Mean Square Error of Approximation (RMSEA) (Rappaport, Amstadter and Neale, 2019).

The evaluation of model fit is crucial in determining how well the proposed model aligns with the observed data, with a good fit indicating that the model accurately represents the relationships among variables in the dataset (Rappaport, Amstadter and Neale, 2019). Upon achieving a satisfactory model fit, researchers proceed to interpret the results generated by SEM, which includes analyzing path coefficients to understand the strength and direction of relationships between variables (Rappaport, Amstadter and Neale, 2019). Additionally, researchers may conduct mediation or moderation analyses to further elucidate the underlying processes influencing the observed associations (Bader and Moshagen, 2022).

In conclusion, SEM is a valuable analytical tool that enables researchers to explore complex relationships among variables by combining measurement and structural model estimation (HairJr. *et al.*, 2021). By utilizing SEM in data analysis, researchers can gain a deeper understanding of the complex interrelationships among variables, ultimately providing valuable insights into the underlying structures and processes influencing the phenomenon under investigation (Belcher *et al.*, 2019). This analytical approach offers flexibility and power in analyzing data across various fields, making it a valuable method for researchers seeking to unravel complex relationships within their datasets.

3.9 Limitations of research design

Structural Equation Modeling (SEM) and the questionnaire method are widely used in quantitative research, each with its own set of limitations. SEM, a statistical technique used to test and estimate causal relationships using observed and latent variables, has several limitations. One key limitation of SEM is the requirement for a relatively large sample size to ensure the model's stability and reliability. This can be challenging in practice, especially when dealing with complex models or limited resources for data collection. Additionally, SEM assumes that the data are normally distributed, which may not always hold true in real-world scenarios, potentially leading to biased results (Zhang, 2017). Moreover, SEM requires a well-defined theoretical model a priori, which can be restrictive as it may not account for unexpected relationships or variables that emerge during the study (Zhang, 2017).

On the other hand, the questionnaire method, commonly used for data collection in quantitative research, also presents its own limitations. One significant limitation of questionnaires is the potential for response bias, where participants may provide inaccurate or socially desirable responses, impacting the validity of the data collected (Katz *et al.*, 2008). This bias can be influenced by factors such as question wording, response options, or the context in which the questionnaire is administered (Katz *et al.*, 2008).

Furthermore, questionnaires rely on self-reported data, which can be subjective and prone to errors due to factors like memory recall or misinterpretation of questions (Katz *et al*., 2008). This subjectivity can introduce measurement error and affect the overall reliability of the study findings.

Another limitation of the questionnaire method is the issue of generalizability. Since questionnaires often rely on convenience or voluntary sampling, the sample may not be representative of the larger population, limiting the external validity of the study (Katz *et al.*, 2008). This lack of generalizability can restrict the applicability of the research findings beyond the specific sample studied.

Additionally, questionnaires may suffer from low response rates, especially in sensitive topics or when participants perceive the survey as too lengthy or burdensome (Katz *et al.*, 2008). Low response rates can introduce non-response bias, where the characteristics of non-respondents differ from those who participate, potentially skewing the results.

In summary, while SEM offers a powerful tool for testing complex relationships in quantitative research, its limitations include the need for large sample sizes, assumptions of normality, and rigid theoretical modeling requirements. On the other hand, the questionnaire method, commonly used for data collection, faces challenges related to response bias, subjectivity in self-reported data, issues of generalizability, and potential low response rates. Researchers employing these methods should be aware of these limitations and take steps to mitigate their impact on the validity and reliability of their study findings.

3.10 Conclusion

The integration of Intelligent Decision Support Systems (IDSS) in organizational settings is a promising avenue for enhancing decision-making processes. However, there is a significant gap in understanding the factors influencing IDSS adoption within organizations. This gap is underscored by the challenges posed by the complexity and volume of data in modern enterprises, the exponential growth of data, and cognitive biases and heuristics. Understanding the determinants that drive the adoption of IDSS is crucial for maximizing their efficacy and organizational impact.

The Technology-Organization-Environment (TOE) framework is a valuable theoretical model for understanding the adoption and implementation of technology within organizations. Operationalizing the constructs within the TOE framework involves translating these factors into measurable variables or indicators that can be empirically assessed. Numerous studies have utilized the TOE framework to investigate technology adoption in various contexts, emphasizing the importance of considering technological, organizational, and environmental factors in adoption processes.

Quantitative methods of data collection are essential in research, providing structured and numerical insights that can be statistically analyzed to draw meaningful conclusions. Quantitative methods enable researchers to measure variables related to technology, organizational characteristics, and external environmental factors, providing a systematic approach to understanding the adoption process. In the realm of education research, quantitative data collection is demonstrated in analyzing digital citizenship of social studies teachers.

The operationalization of quantitative data collection methods is essential for conducting rigorous and systematic research across diverse disciplines. By employing quantitative approaches, researchers can gather numerical data, analyze patterns and trends, and derive evidence-based conclusions, thereby advancing knowledge and contributing to evidence-informed decision-making processes.

The Indian Micro, Small, and Medium Enterprises (MSME) sector, which comprises around 26 million firms and employs around 60 million individuals, is a significant indicator of the country's economic landscape. These enterprises contribute about 8% to the Indian GDP and represent about 95% of the enterprises in India. The development of the MSME sector in India is crucial for economic growth and employment generation, as it plays a vital role in promoting inclusive growth and leveraging India's demographic dividend. SMEs are a dynamic engine of growth in India, contributing significantly to eradicating unemployment, poverty, income inequality, and regional imbalances.

A diverse sample of 508 participants across India was selected using appropriate sampling techniques, considering industry sectors, organizational sizes, and geographical regions. Random sampling is a fundamental method in research to ensure the representativeness of a sample from a larger population, aiming to minimize bias and enhance the generalizability of findings. Various methods of random sampling exist, such as simple random sampling, stratified random sampling, and cluster sampling, with the choice depending on factors like research objectives and available resources.

After data collection, researchers analyze the sample to draw conclusions about the population, often employing statistical techniques for inference. The ultimate goal of random sampling is to generalize findings from the sample to the entire population, emphasizing the importance of a representative sample and rigorous sampling processes. By adhering to principles of randomness and employing appropriate sampling techniques, researchers can increase the robustness of their research outcomes and make more accurate inferences about the broader population.

The research utilized a survey-based instrument method to collect data, which involved a questionnaire designed to gather relevant information from a targeted sample of individuals. This method was carefully designed to minimize bias and ensure the validity and reliability of the collected data.

The data collection procedure involved a multi-faceted approach, including simple random sampling, online and offline methods, a network of networks, and snowball sampling techniques. This ensured the inclusion of a diverse range of participants and perspectives, enhancing the validity and reliability of the research findings.

Structural Equation Modeling (SEM) was used as a statistical technique to explore and validate complex relationships among variables by analyzing both observed and latent variables. The process involves model specification, measurement model estimation, structural model estimation, and interpreting the results generated by SEM.

Model specification is the first step in employing SEM, where researchers outline a theoretical model illustrating the proposed relationships among the variables of interest. The measurement model estimation stage evaluates the relationships between observed variables and their corresponding latent constructs, while structural model estimation examines the relationships between latent variables and tests the specified paths or hypotheses within the theoretical model.

After achieving a satisfactory model fit, researchers interpret the results generated by SEM, analyzing path coefficients to understand the strength and direction of relationships between variables. Mediation or moderation analyses may also be conducted to further elucidate the underlying processes influencing the observed associations.

SEM is a valuable analytical tool that enables researchers to explore complex relationships among variables by combining measurement and structural model estimation. This approach offers flexibility and power in analyzing data across various fields, making it a valuable method for researchers seeking to unravel complex relationships within their datasets.

CHAPTER IV:
RESULTS

4.1 Confirmatory Factor Analysis

Convergent validity

The study measures both the convergent validity and discriminant validity of the measurement variables used in the model. The convergent validity includes factor-loadings >0.70 and average variance extracted (AVE) >0.50 (Joseph F. Hair *et al.*, 2010) . On the other hand, the discriminant validity includes the criteria of Fornell-Larcker which suggests that the value of one variable should be higher with itself in the same column (Fornell and F.Larcker, 2012). Factor loadings and average variance extracted (AVE) are used to quantify the constructs' convergent validity (Becker, Klein and Wetzels, 2012). The link between the observable variables (or items) and the latent variables (factors) is displayed via factor loadings. A high loading indicates that the observable variable significantly contributes to the latent variable. Previous research often provides threshold values as benchmarks for assessing the importance of various loadings. Several research studies have indicated that factor loadings should be more than 0.5 to obtain better results (Truong and Mccoll, 2011). However, (Chen and Tsai, 2007) also believed that 0.5 represented the threshold for acceptable loadings. Additionally, (Ertz, Karakas and Sarigöllü, 2016) considered factor loadings of 0.4 and higher in their confirmatory factor analysis. Because of this, in addition to the fact that 0.6 is better than the factor loading cut-offs employed in this research, the study chose the criterion of 0.6 or higher factor loadings (Joseph F. Hair *et al.*, 2010). The standardized loading of variables for all item ranges was above the 0.6 threshold limit.

The research employs a sequential approach to conducting confirmatory factor analysis (CFA) using AMOS, aiming to attain factor loadings greater than 0.6. The study found that 5 items of relative advantage (RA1, RA5, RA6, RA7, RA8), 3 items of complexity (COX3, COX10, COX11), 4 items of compatibility (COM1, COM2, COM3 COM4), 3 items of top management support (TMS5, TMS6 TMS7), 4 items of technology readiness (TR1,TR5, TR6, TR7), 4 items of environmental factor (ENV1, ENV2, ENV5,ENV8) had lower threshold from 0.06 and they were removed from the model (see figure 3.1).

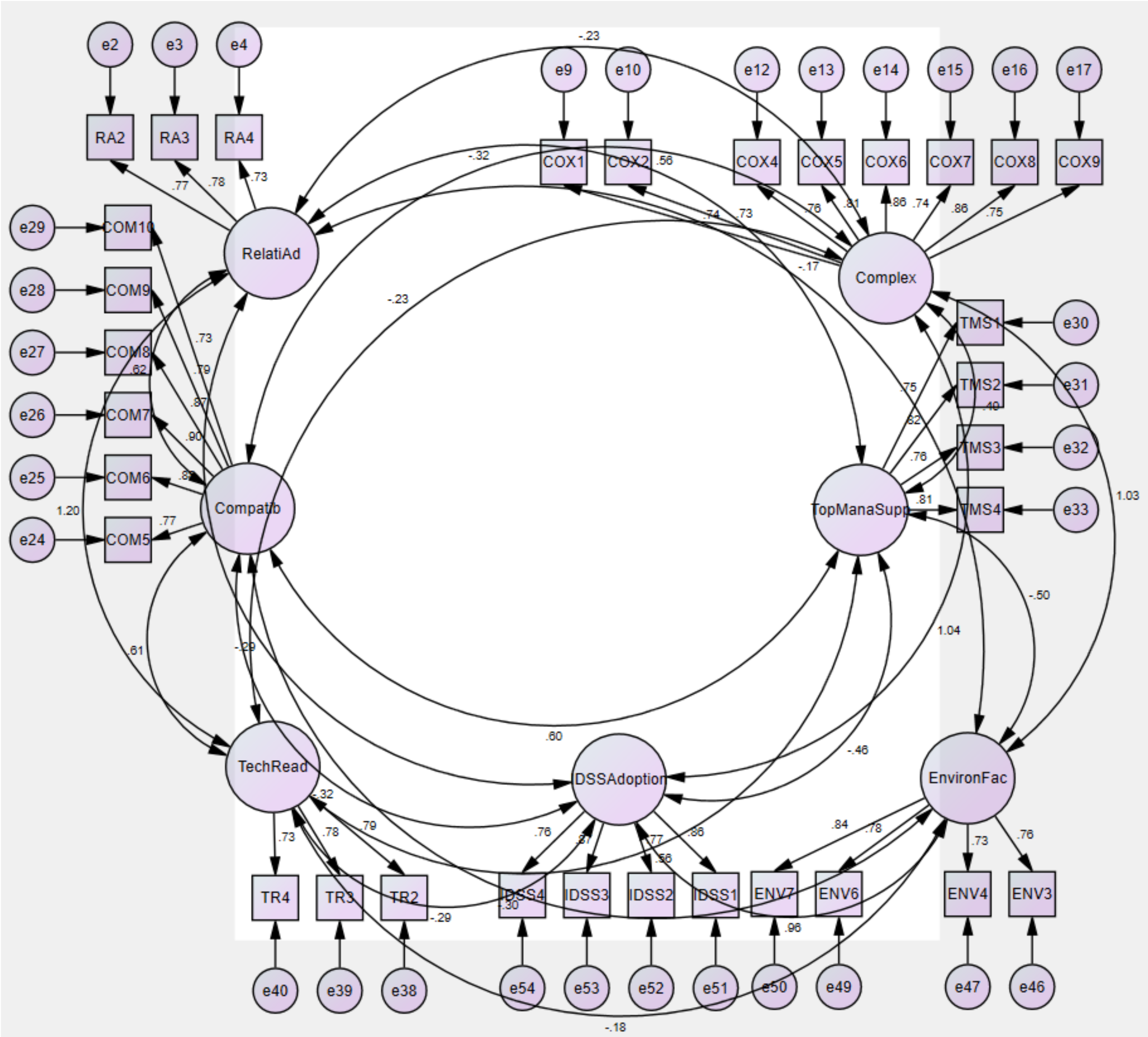

Figure 2 Confirmatory factor analysis (CFA)

Following (Joseph F. Hair *et al.*, 2010) methodological guidelines, factor loadings for each construct are assessed in the structural model shown, with a benchmark set above 0.60. The items in the construct 'Complexity' exhibit a significant relationship with it; all loadings are higher than the 0.60 threshold, supporting the idea that these items are reasonable measures of complexity in the model. A significant correlation between the "IDSS Adoption" construct and its observable variables may also be shown, as high factor loadings that satisfy the predetermined conditions demonstrate. Among them, one item has a loading that is noticeably higher than 0.60, indicating a strong representation of the construct.

As the 'technology readiness' construct is examined, the loading of the associated items shows a strong and constant link, indicating that these items represent the essence of technological preparedness within the study's setting. The items about the constructs of "compatibility" also satisfy the 0.60 standards, indicating their suitability for measuring the relevant theoretical notions. The substantial association between the latent variable and the factor loadings associated with the items under 'top management support' underscores the significance and potency of the construct in the model. All the items just exceed the cutoff, consistent with the stringent analytical methodology (Joseph F. Hair *et al.*, 2010) recommended. The items "environmental factor" and "relative advantage" exhibit loadings over the 0.60 cutoff, indicating that they accurately represent the corresponding constructs. In particular, one item has a very high loading, highlighting its significance in the build and the model overall.

Moreover, only TR5 items associated with the "technology readiness" construct had loadings lower than the benchmark; one item, in particular, had a very high loading, clearly suggesting technological readiness. This observation aligns with the norms for measuring constructs in strategic management research. Lastly, the items that make up the 'Complexity' construct show loadings that are consistently higher than the threshold, confirming their status as trustworthy markers of complexity within the framework of the study. Every item's loading, especially those noticeably higher than 0.60, highlights the measurement's robustness and the constructs' measurements.

The factor loadings for the constructs are over the 0.60 level, indicating satisfactory convergent validity according to (Joseph F. Hair *et al.*, 2010) strict standards for multivariate data analysis. This shows that the model is well-defined regarding the connections between constructs and their measures and that the items are appropriate indicators of the corresponding constructs.

Table 1 Factor loadings

Loadings		**Constructs**	**Estimate**
RA2	<---	Relative Advantage	.768
RA3	<---	Relative Advantage	.734
RA4	<---	Relative Advantage	.775
COX1	<---	Complexity	.737

COX2	<---	Complexity	.734
COX4	<---	Complexity	.762
COX5	<---	Complexity	.813
COX6	<---	Complexity	.856
COX7	<---	Complexity	.744
COX8	<---	Complexity	.864
COX9	<---	Complexity	.747
COM5	<---	Compatibility	.770
COM6	<---	Compatibility	.881
COM7	<---	Compatibility	.905
COM8	<---	Compatibility	.871
COM9	<---	Compatibility	.795
COM10	<---	Compatibility	.730
TR2	<---	Technology Readiness	.787
TR3	<---	Technology Readiness	.785
TR4	<---	Technology Readiness	.731
TMS1	<---	Top Management Support	.747
TMS2	<---	Top Management Support	.816
TMS3	<---	Top Management Support	.764
TMS4	<---	Top Management Support	.806
ENV3	<---	Environmental Factor	.762
ENV4	<---	Environmental Factor	.733
ENV6	<---	Environmental Factor	.784
ENV7	<---	Environmental Factor	.835
IDSS	<---	IDSS Adoption	.859
IDSS	<---	IDSS Adoption	.767
IDSS	<---	IDSS Adoption	.866
IDSS	<---	IDSS Adoption	.765

Average variance extracted (AVE)

A crucial statistical metric for confirming the convergent validity of the measuring scales is the average variance extracted (AVE). As shown in Table 2, AVE measures the degree to which a construct accounts for the variations of its observed variables relative to the variance resulting from measurement error. It is essential for confirming the validity of the construct, mainly convergent validity. Sarstedt et al. (2019) state that a construct's AVE must be more than 0.50 to be deemed legitimate. Using this criterion guarantees that the construct explains more than half of the measurement variation. If the AVE value is less than 0.50, it could suggest that measurement error outweighs the construct's explanation ability.

The AVE values for the constructs range from 0.576 to 0.685, indicating a range of convergent validity among the components. The constructs that demonstrate the highest AVEs are 'Compatibility' (0.685), indicating that the measurements are consistent with the constructs they intend to represent. Conversely, 'Relative Advantage' shows an AVE of 0.576, somewhat beyond the allowable limit, indicating a marginally poorer but respectable cohesion between its indicators. A robust representation of the variance within each indication is indicated by the AVE values of other constructs, namely 'Technology Readiness' (0.590), 'Top Management Support' (0.614), and 'Environmental Factor' (0.607), mainly by the constructions themselves. This validates the model's validity and aligns with the PLS-SEM criteria underlined by experts like (Henseler and Chin, 2010). 'IDSS' also has an AVE of 0.665, which lends more credence to the idea that the model's indicators agree with the concepts they stand for. This facet of model validation aligns with the methodological guidelines suggested by (Richter *et al.*, 2016) and (Latan and Noonan, 2017). It emphasizes the importance of AVE in PLS-SEM, even in various study contexts.

The AVE values that have been presented validate the study's integrity in proving construct validity. They demonstrate that the model's constructs and indicators accurately reflect one another, thereby demonstrating the convergent validity of the study.

Table 2 Average variance extracted (AVE)

Constructs	Average Variance Extracted (AVE)
Relative Advantage	0.576
Complexity	0.614
Compatibility	0.685
Technology Readiness	0.590
Top Management Support	0.614
Environmental Factor	0.607
IDSS Adoption	0.665

Discriminant validity

Traditional discriminant validity testing uses the Fornell-Larcker criterion to ensure that a construct is distinct from others in the model. Discriminant validity is established when the square root of the average variance extracted (AVE) for each construct is greater than its correlations with other model constructs, according to (Fornell and F.Larcker, 2012). Since the diagonal elements in the table are all less than 1 but close to it, they likely represent the square roots of the constructs' AVEs, indicating strong construct reliability.

Most constructs have higher diagonal values (square root of AVE) than off-diagonal correlations, supporting discriminant validity. The highest correlation of Environmental Factor (0.779) is with IDSS Adoption (0.756). This pattern is consistent, with Relative Advantage (0.759) having a lower correlation with Technology Readiness (0.701). Some correlations, like Environmental Factor and Complexity (0.632), approach the AVE values, suggesting discriminant validity issues for those constructs. Due to their proximity, these constructs may overlap in conceptual definitions or measurement, requiring a review of the measurement items or model specifications.

Thus, while the model generally meets the Fornell-Larcker criterion for discriminant validity, high correlations near the threshold for a few constructs suggest caution. To ensure that each construct captures its theoretical domain without overlap, the measurement or conceptual framework may need to be adjusted. To make the SEM model robust and interpretable and ensure that analysis conclusions are based on well-defined theoretical constructs, this step is essential.

Table 3 Fornell Larcker Criteria

Constructs	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Environmental Factor	0.779						
Relative Advantage	-0.170	0.759					
Complexity	0.632	-0.229	0.784				
Compatibility	-0.298	0.619	-0.323	0.828			
Top Management Support	-0.501	0.561	-0.488	0.605	0.784		
Technology Readiness	-0.175	0.701	-0.234	0.607	0.564	0.768	
IDSS Adoption	0.756	-0.290	0.737	-0.320	-0.460	-0.294	0.816

Composite reliability

The measures' reliability determines how well the consistency and stability of the constructs in a study are evaluated. Table 3.4 shows that composite reliability (CR) is a crucial metric for this purpose since it evaluates the internal consistency of reflective constructions. It is generally agreed that a reliability criterion of 0.7 indicates adequate dependability (Joseph F. Hair *et al.*, 2010; Latan and Noonan, 2017). Each construct exceeds this cutoff, as indicated by the values in Table 4, confirming the strong internal consistency of the measurements used in the study. Each construct has a composite reliability score higher than the predetermined threshold of 0.7, indicating that the measurement models are reliable. For example, the constructs 'Compatibility' and 'Complexity' have a very high CR (0.929, 0.927 respectively), indicating the robustness of their internal consistency. With a CR of 0.888, "IDSS Adoption" likewise exhibits strong dependability, boosting the trustworthiness of these measurements.

Because it considers the varying factor loadings of construct indicators, composite reliability is considered a more rigorous reliability metric than other traditional measures. This allows for a more sophisticated understanding of internal consistency. This is especially important for constructs that are measured using several items, each of which may contribute less evenly to the construct's variance. Not only do the recorded CR values surpass the acceptable thresholds for each construct, but they do so with a margin that bolsters the study's reliability claim. One example of high reliability is "Top Management Support," which has a CR of 0.864. The CRs for “Environmental Factor 0.861”, indicating strong measurement models.

The measurements are made more reliable by constantly surpassing the CR benchmark across all constructions. The study's high composite reliability raises the overall caliber and legitimacy of the results by offering a solid foundation for the following analyses and interpretations. The thorough evaluation of composite reliability guarantees a solid methodological basis for the investigation.

Table 4 Composite reliability

Constructs	Composite Reliability (CR)
Relative Advantage	0.803
Complexity	0.927
Compatibility	0.929
Technology Readiness	0.812
Top Management Support	0.864
Environmental Factor	0.861
IDSS Adoption	0.888

Evaluation of Model Fit Indices

Table 5 encapsulates the assessment of the model fit indices for the tourism model analyzed in this study. The study adheres to established benchmark values for a range of fit criteria. A key measure of fit, the relative chi-square (CMIN/DF), is reported at 18.920 for the model under consideration. Commonly accepted standards, such as those posited by (Kline, 2011), posit that a value below 5 indicates a sound model fit. Hence, our model's CMIN/DF value significantly exceeds the recommended threshold, suggesting the model may not fit the data as well as desired. The Root Mean Square Residual (RMR), indicating the disparity between the sampled and estimated covariance matrices, stands at 0.239. Lower RMR values are preferable, with the ideal being close to zero, as per the guidelines of (Hu and Bentler, 1999). This higher RMR value suggests room for improvement in the model's fit to the observed data.

Further, the model's Goodness of Fit Index (GFI) is observed at 0.547. While GFI values span from 0 to 1, with values closer to 1 representing a superior fit, the literature, including (Jöreskog and Sörbom, 1993), typically recommends a threshold above 0.90 for a robust fit, which our model does not achieve, indicating a less than optimal fit. In examining incremental fit indices, this model records values for the Normed Fit Index (NFI), Relative Fit Index (RFI), Tucker-Lewis Index (TLI), and Comparative Fit Index (CFI) as 0.607, 0.560, 0.574, and 0.619, respectively. As (Bentler and Bonett, 1980) suggest, these indices ideally approach 0.95 to reflect a good fit. Although our model's values fall below this benchmark, they provide some evidence of fit, albeit not at the levels considered ideal. Lastly, the Root Mean Square Error of Approximation (RMSEA), which assesses the deviation between the hypothesized model with optimal parameter estimates and the population covariance matrix, shows a value of 0.189. Values below 0.08 are recommended by (Browne and Cudeck, 1992) for a good fit, and thus, the model's RMSEA value significantly surpasses this, suggesting the fit could be substantially improved. While some model fit indices meet the minimum criteria, others fall short, resulting in an overall model fit that aligns partially with conventional acceptance levels. As per these indices, the model may require re-evaluation or adjustment to improve fit to the data. Despite these challenges, the fit indices serve as a guide and starting point for further model refinement.

Table 5 *Model fit indices*

Fit Indices	CMIN/DF	RMR	GFI	NFI	RFI	TLI	CFI	RMSEA
Values	18.920	.239	.547	.607	.560	.574	.619	.189
p-values	.000	.000	.000	.000	.000	.000	.000	.000

Notes: CMIN/DF = Chi-Square to Degrees of Freedom Ratio, RMR = Root Mean Square Residual, GFI = Goodness of Fit Index, NFI = Normed Fit Index, RFI = Relative fit index, TLI = Tucker-Lewis Index, CFI = Comparative Fit Index, RMSEA = Root Mean Square Error of Approximation

4.2 Structural Equation Modeling (SEM)

The complexity and multi-dimensionality of the theoretical model being tested justify the use of Structural Equation Modeling (SEM) in AMOS to analyze the relationship between various factors and IDSS adoption (See Table 6, Figure3). SEM can estimate multiple and interrelated dependence relationships simultaneously, providing an understanding of IDSS adoption paths. SEM is robust in measurement and error estimation for latent constructs measured indirectly by multiple variables (Joseph F. Hair *et al.*, 2010). The path coefficient (β), standard error (S.E.), and p-value are crucial statistics in SEM for evaluating hypotheses. The path coefficient indicates the strength and direction of the relationship, while the standard error measures the accuracy of the β estimates. The p-value tests the null hypothesis of zero statically significant p-values are less than .05, but stricter thresholds (.01, .001) indicate stronger evidence against the null hypothesis (Kline, 2011).

The SEM approach follows structural relationship analysis best practices, especially in technology adoption research. The path coefficients (β) from SEM estimate the impact of each predictor on the outcome, while the associated standard errors (S.E.) assess the reliability of these estimates. Researchers use p-values (***, **, * for p-values <.001, <.01, <.05) to assess the robustness of their theoretical model's relationships. SEM in AMOS fits the model to the data, which is evaluated using goodness-of-fit indices like RMSEA, CFI, and TLI to validate structural assumptions (Byrne, 2016). Thus, SEM supports nuanced analysis of complex models and aligns with social sciences research methodological standards, providing clarity and precision in understanding IDSS adoption factors.

Hypothesis Development

Hypothesis 1

H_0: There is no significant relationship between IDSS adoption and relative advantage

H_A: There is a significant relationship between IDSS adoption and relative advantage

The findings for hypothesis H1 [Relative Advantage → IDSS Adoption], with a path coefficient (β) of [-.013] and a standard error (SE) of [.067], and a p-value of [.850], indicate a weak and non-significant relationship. Thus, alternative hypothesis is rejected. This suggests that relative advantage does not significantly influence IDSS adoption, leading us to not accept H1.

Hypothesis 2

H_0: There is no significant relationship between IDSS adoption and complexity

H_A: There is a significant relationship between IDSS adoption and complexity

Hypothesis H2 [Complexity → IDSS Adoption] presents a significant positive relationship with a path coefficient (β) of [1.363] and a notably small standard error (SE) of [.044]. The asterisks [***] denote a p-value small enough to be highly significant, strongly suggesting that complexity substantially and positively affects IDSS adoption. Thus, null hypothesis is rejected. This result supports the acceptance of H2, indicating that, in this context, greater complexity may be associated with perceived benefits that encourage adoption.

Hypothesis 3

H_0: There is no significant relationship between IDSS adoption and compatibility

H_A: There is a significant relationship between IDSS adoption and compatibility

In H3 [Compatibility → IDSS Adoption], the path coefficient (β) is [.009] with a standard error (SE) of [.019] and a p-value of [.633]. Thus, alternative hypothesis is rejected. The non-significant p-value suggests a weak relationship, leading to the rejection of H3, indicating that compatibility may not significantly influence the adoption of IDSS in this instance.

Hypothesis 4

H_0: There is no significant relationship between IDSS adoption and top management support

H_A: There is a significant relationship between IDSS adoption and top management support

H4 [Top Management Support → IDSS Adoption] shows a β of [.034] and an SE of [.018], with a marginally significant p-value of [.064]. Thus, alternative hypothesis is rejected. This indicates a potential but not strong influence of top management support on IDSS adoption, leaving the acceptance of this hypothesis uncertain without stronger statistical evidence.

Hypothesis 5

H_0: There is no significant relationship between IDSS adoption and firm characteristics

H_A: There is a significant relationship between IDSS adoption and firm characteristics

Hypothesis H5 [Firm Characteristics → IDSS Adoption], with a β of [.016] and an SE of [.067], coupled with a high p-value of [.808], indicates no significant relationship. Thus, alternative hypothesis is rejected. This leads to the rejection of H5, implying that firm size does not significantly affect IDSS adoption.

Hypothesis 6

H_0: There is no significant relationship between IDSS adoption and technology readiness

H_A: There is a significant relationship between IDSS adoption and technology readiness

In H6 [Technology Readiness → IDSS Adoption], the β of [-.077] and an SE of [.066] suggest a slight negative impact, with a p-value of [.244]. Thus, alternative hypothesis is rejected. This result indicates a non-significant relationship, leading to the rejection of H6, suggesting that technology readiness does not significantly affect IDSS adoption.

Hypothesis 7

H_0: There is no significant relationship between IDSS adoption and environmental factors

H_A: There is a significant relationship between IDSS adoption and environmental factors

Hypothesis H7 [Environmental Factor → IDSS Adoption] shows a substantial negative β of [-.351] with a very small SE of [.043], and the asterisks [***] indicate a highly significant p-value. Thus, null hypothesis is rejected. This strong negative relationship leads to the acceptance of H7, suggesting that environmental factor may significantly discourage IDSS adoption, perhaps due to challenges or constraints imposed by these factors.

Table 6 Structural equation modeling

Hypotheses	**Path Coefficient (β)**	**Std. Error (SE)**	**p-value**	**Significance**
H1: Relative Advantage → IDSS Adoption	-.013	.067	.850	
H2: Complexity → IDSS Adoption	1.363	.044	***	*
H3: Compatibility → IDSS Adoption	.009	.019	.633	
H4: Top Management Support → IDSS Adoption	.034	.018	.064	
H5: Firm Size → IDSS Adoption	.016	.067	.808	
H6: Technology Readiness → IDSS Adoption	-.077	.066	.244	
H7: Environmental Factor → IDSS Adoption	-.351	.043	***	*

Note: (***, **, * for p-values <.001, <.01, <.05)

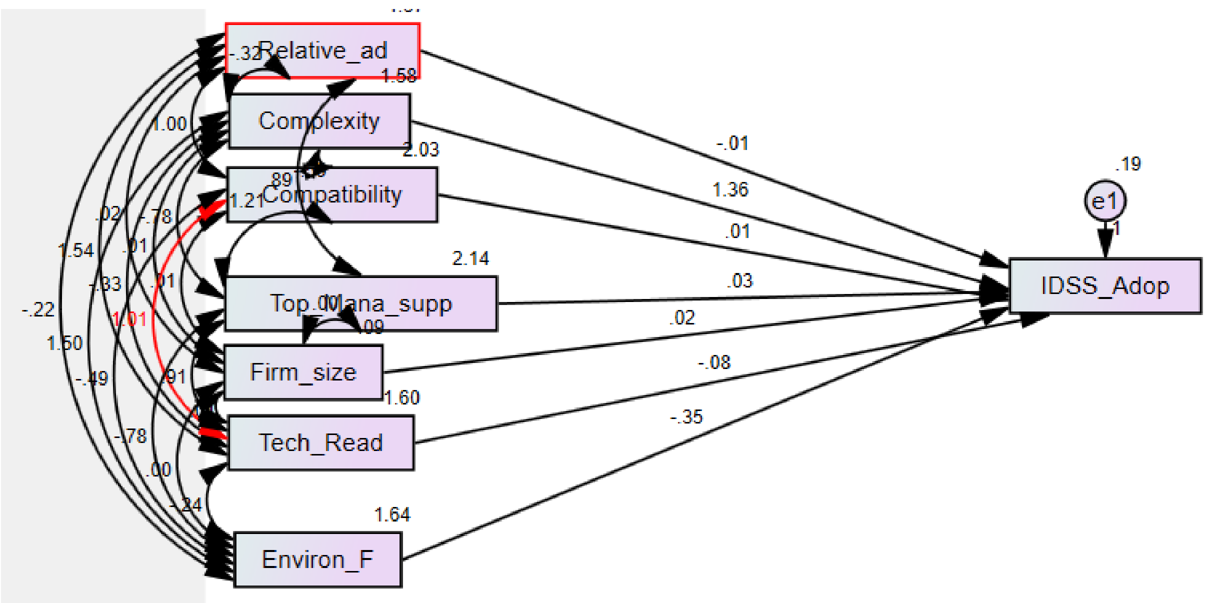

Figure 3 Structural Equation Modeling

Model fit indices

The SEM model fit indices presented in Table 7 provide a mixed assessment of the model's adequacy. The extremely high CMIN/DF value of 149.695 significantly exceeds the commonly acceptable thresholds of less than 3 or 5, suggesting a poor model fit the data, while the p-value of .000 indicates statistical significance in this misfit. However, other indices like the RMR, GFI, NFI, TLI, and CFI all report perfect scores of 1.000 or close to zero for RMR, implying an excellent fit. This could suggest that the model is overfitting or that specific aspects of the model structure need re-evaluation. The RMSEA value of .543, which is well above the acceptable upper limit of .08, further supports the notion of a poor fit, indicating substantial approximation errors. Thus, while certain aspects of the model suggest an ideal fit, the high CMIN/DF and RMSEA values critically challenge the model's validity, highlighting the need for model re-specification or adjustment to better capture the underlying data structure.

Table 7 Model fit indices

Fit Indices	**CMIN/DF**	**RMR**	**GFI**	**NFI**	**RFI**	**TLI**	**CFI**	**RMSEA**
Values	149.695	.000	1.000	1.000	.000	1.000	1.000	.543
p-values	.000	.000	.000	.000	.000	.000	.000	.000

Notes: CMIN/DF = Chi-Square to Degrees of Freedom Ratio, RMR = Root Mean Square Residual, GFI = Goodness of Fit Index, NFI = Normed Fit Index, RFI = Relative fit index, TLI

= Tucker-Lewis Index, CFI = Comparative Fit Index, RMSEA = Root Mean Square Error of Approximation

4.3 Summary of results

The study measures both convergent and discriminant validity of measurement variables used in the model. Convergent validity includes factor-loadings >0.70 and average variance extracted (AVE) >0.50, while discriminant validity includes Fornell-Larcker's criteria. Factor loadings and average variance extracted (AVE) are used to quantify the constructs' convergent validity. A high loading indicates that the observable variable significantly contributes to the latent variable.

The research employs a sequential approach to confirmatory factor analysis (CFA) using AMOS, aiming to attain factor loadings greater than 0.6. The study found that 5 items of relative advantage, 3 items of complexity, 4 items of compatibility, 3 items of top management support, 4 items of technology readiness, and 4 items of environmental factor had lower thresholds from 0.06 and were removed from the model.

Following Joseph F. Hair et al. (2010) methodological guidelines, factor loadings for each construct are assessed in the structural model shown, with a benchmark set above 0.60. The items in the construct 'Complexity' exhibit a significant relationship with it, all loadings are higher than the 0.60 threshold, supporting the idea that these items are reasonable measures of complexity in the model.

The items "environmental factor" and "relative advantage" exhibit loadings over the 0.60 cutoff, indicating that they accurately represent the corresponding constructs. The factor loadings for the constructs are over the 0.60 level, indicating satisfactory convergent validity according to Joseph F. Hair et al. (2010) strict standards for multivariate data analysis.

The average variance extracted (AVE) is a crucial statistical metric for confirming the convergent validity of measuring scales. It measures the degree to which a construct accounts for variations in observed variables relative to the variance resulting from measurement error. A construct's AVE must be more than 0.50 to be deemed legitimate, ensuring that the construct explains more than half of the measurement variation. The AVE values for the constructs range from 0.576 to 0.685, indicating a range of convergent validity among the components.

The Fornell-Larcker criterion is used to ensure that a construct is distinct from others in the model. Most constructs have higher diagonal values than off-diagonal correlations, supporting discriminant validity. The highest correlation of Environmental Factor is with IDSS Adoption (0.756), while Relative Advantage (0.759) has a lower correlation with Technology Readiness (0.701). High correlations near the threshold for a few constructs suggest caution.

Composite reliability (CR) is a crucial metric for evaluating the internal consistency of reflective constructions. Each construct exceeds the predetermined threshold of 0.7, confirming the strong internal consistency of the measurements used in the study. The composite reliability score higher than the predetermined threshold of 0.7 indicates that the measurement models are reliable.

The study's high composite reliability raises the overall caliber and legitimacy of the results by offering a solid foundation for the following analyses and interpretations. The thorough evaluation of composite reliability guarantees a solid methodological basis for the investigation.

The study evaluates the model fit indices for a tourism destination model, adhering to established benchmark values. The model's relative chi-square (CMIN/DF) value exceeds the recommended threshold, suggesting the model may not fit the data as well as desired. The Root Mean Square Residual (RMR) value is higher than the recommended threshold, suggesting room for improvement. The Goodness of Fit Index (GFI) value is 0.547, indicating a less than optimal fit. The Normed Fit Index (NFI), Relative Fit Index (RFI), Tucker-Lewis Index (TLI), and Comparative Fit Index (CFI) values are 0.607, 0.560, 0.574, and 0.619, respectively. The Root Mean Square Error of Approximation (RMSEA) value is 0.189, suggesting the fit could be substantially improved.

Structural Equation Modeling (SEM) is used to analyze the relationship between various factors and IDSS adoption. SEM can estimate multiple and interrelated dependence relationships simultaneously, providing an understanding of IDSS adoption paths. The path coefficient, standard error, and p-value are crucial statistics for evaluating hypotheses. SEM aligns with social sciences research methodological standards, providing clarity and precision in understanding IDSS adoption factors.

The study examines the relationship between relative advantage, complexity, compatibility, top management support, firm size, technology readiness, and environmental factors in promoting Intelligent Decision Support Systems (IDSS) adoption. The results show a weak and non-significant relationship between these variables, with a path coefficient of -.013 and a standard error of -.067. Complexity showed a significant positive relationship, suggesting that greater complexity may be associated with perceived benefits. Compatibility showed a weak relationship, suggesting compatibility may not significantly influence IDSS adoption. Top management support showed a potential but not strong influence, leaving the acceptance of this hypothesis uncertain without stronger statistical evidence. Firm size did not significantly affect IDSS adoption, while technology readiness did not significantly affect IDSS adoption. Environmental factors, such as challenges or constraints imposed by these factors, may discourage IDSS adoption. The SEM model fit indices provide mixed assessments of the model's adequacy, with a high CMIN/DF value of 149.695 suggesting a poor model fit, while other indices like the RMR, GFI, NFI, TLI, and CFI all report perfect scores of 1.000 or close to zero for RMR. The RMSEA value of.543 further supports the notion of a poor fit, indicating substantial approximation errors.

CHAPTER V:
DISCUSSION

5.1 Existing literature on challenges in Artificial intelligence tools adoption by Small and medium enterprises in India

Small and Medium Enterprises (SMEs) in India encounter specific challenges in adopting artificial intelligence (AI) technologies, and the Technology-Organisation-Environment (TOE) framework can offer valuable insights into these obstacles. The TOE framework, as utilized in studies such as (Sharma et al., 2024), provides a structured approach to comprehending how technology, organizational factors, and the external environment interact to impact AI adoption in SMEs. In the Indian context, where SMEs play a vital role in the economy, integrating AI technologies like chatbots, AI-CRM capabilities, and big data analytics is crucial for maintaining competitiveness in a rapidly evolving market landscape (Chatterjee et al., 2021; Maroufkhani et al., 2022).

One of the primary challenges faced by SMEs in India regarding AI adoption is the lack of awareness and understanding of AI technologies and their potential benefits. Many SMEs may view AI as complex, costly, or irrelevant to their business operations, leading to hesitancy in adoption (Suresh et al., 2023). Additionally, the scarcity of skilled personnel proficient in AI technologies poses a significant barrier for SMEs seeking to incorporate AI into their processes. Without access to talent with expertise in AI, SMEs may encounter difficulties in implementing and leveraging AI solutions effectively (Sharma et al., 2024).

Financial constraints also present a significant challenge for SMEs in India considering AI adoption. Implementing AI technologies often demands a substantial initial investment in infrastructure, software, and training. For SMEs operating on tight budgets, allocating resources to AI projects can be daunting, particularly when the return on investment is not immediately apparent (Suresh et al., 2023). This financial barrier can impede SMEs from exploring the full potential of AI in enhancing their operational efficiency and competitiveness.

Furthermore, the regulatory environment in India may pose challenges for SMEs venturing into AI adoption. The absence of clear guidelines or policies related to AI implementation and data privacy can create uncertainty and compliance risks for SMEs (Chatterjee et al., 2021). Concerns about data security, privacy regulations, and ethical considerations surrounding AI use may discourage SMEs from fully embracing AI technologies, fearing legal repercussions or reputational damage (Maroufkhani et al., 2022).

Cultural factors also influence AI adoption among SMEs in India. Traditional business practices and a reluctance to change may hinder the willingness of SME owners and decision-makers to adopt AI technologies (Sharma et al., 2024). Overcoming cultural resistance to innovation and fostering a culture of experimentation and learning are essential for SMEs to successfully integrate AI into their operations and unlock its transformative potential.

In addition to these challenges, the scalability and customization of AI solutions to suit the specific needs and scale of SMEs in India present another hurdle. Many off-the-shelf AI products may not align perfectly with the unique requirements and constraints of SMEs, necessitating customization and integration efforts that can be resource-intensive and time-consuming (Suresh et al., 2023). Finding AI solutions that are affordable, scalable, and tailored to the context of SMEs in India is crucial for driving widespread adoption and maximizing the benefits of AI technologies.

In conclusion, SMEs in India face a variety of challenges in adopting artificial intelligence, encompassing issues related to awareness, talent, finances, regulations, culture, and customization. By leveraging the insights provided by the TOE framework and addressing these challenges systematically, SMEs can navigate the complexities of AI adoption more effectively and harness the transformative power of AI to drive innovation, growth, and competitiveness in the Indian business landscape.

5.2 Discussion on the findings of Thesis

The limitation of structural equation modeling (SEM) and confirmatory factor analysis (CFA) to completely satisfy the fitness tests when assessing the impact of complexity and environmental factors on IDSS adoption highlights a limitation in the current methodologies used to analyze these relationships (Huang, 2022). This limitation underscores the need for future research to explore alternative modeling techniques that can effectively capture the intricate interplay between technology, organization, environment, and the identified complexity factors in the adoption of IDSS within Indian SMEs.

Nevertheless, this thesis discusses on the factors influencing the adoption of intelligent decision support systems, it is crucial to delve into both the complexity factors and environmental factors that can impact organizations. Complexity factors encompass various challenges such as malfunctions, artificial intelligence bias, human emotion disadvantages, security and privacy issues, job replacement concerns, the complexity of adoption, artificial intelligence self-learning capabilities, and employee non-cooperation. These factors can significantly hinder the successful implementation of intelligent decision support systems within organizations (Miller, 2019).

Malfunctions in the system can lead to distrust among users and stakeholders, affecting the overall adoption rate. Additionally, issues related to bias in artificial intelligence algorithms can result in unfair decision-making processes, further complicating adoption efforts. Human emotion disadvantages and job replacement concerns may lead to resistance from employees who fear being replaced by automated systems, impacting the organizational culture negatively.

Moreover, security and privacy issues pose a significant threat, especially in industries dealing with sensitive data, requiring robust measures to address these concerns (Ribeiro et al., 2021).

Furthermore, the complexity of adoption itself, including the integration of new technologies and processes, can be a barrier that organizations need to navigate. The self-learning aspect of artificial intelligence introduces a level of unpredictability that organizations must manage effectively. Employee non-cooperation can arise due to a lack of understanding or training, emphasizing the importance of change management strategies in the adoption process (Jia et al., 2022).

On the other hand, environmental factors play a pivotal role in shaping the adoption landscape of intelligent decision support systems. Influences from competitors, pressures to adopt new technologies, the need for business stakeholder approval, and customer demands can all impact the decision-making process within organizations. Competitor influence can drive organizations to stay competitive by adopting advanced systems, while external pressures may force adoption even if internal readiness is lacking (Yang, 2023).

Moreover, obtaining approval from key stakeholders within the organization is essential for successful implementation. Resistance from stakeholders can impede progress and lead to delays or even failure in adopting intelligent decision support systems.

Customer influence, driven by evolving preferences and expectations, can push organizations to enhance their decision-making capabilities to meet market demands effectively (Zhao & Saeed, 2022). In considering how the study on factors influencing the adoption of intelligent decision support systems can benefit various stakeholders, including industry, government, and educationists, it is essential to highlight the potential positive outcomes.

By addressing and mitigating complexity and environmental factors, organizations can streamline decision-making processes, improve efficiency, and gain a competitive edge in the market. Industry players stand to benefit from enhanced operational performance and strategic decision-making capabilities (Oliveira & Neto, 2023).

Government entities can leverage intelligent decision support systems to optimize public services, allocate resources more effectively, and enhance policy formulation processes. By embracing these technologies, governments can foster innovation and improve governance practices.

Overall, by understanding and addressing the challenges posed by complexity and environmental factors in the adoption of intelligent decision support systems, organizations can unlock a myriad of opportunities for growth, innovation, and sustainable development. Through strategic planning, stakeholder engagement, and continuous learning, the potential benefits of these systems can be fully realized across various sectors, ultimately driving progress and success in the digital era.

CHAPTER VI:
SUMMARY, IMPLICATIONS AND RECDOMMENDATIONS

6.1 Summary

The Technology-Organization-Environment (TOE) framework is a widely used model for understanding the factors influencing technology adoption in organizations. It considers three key factors: complexity, compatibility, relative advantage, and organization. Decision support systems (DSS) have evolved to provide intelligent assistance to decision-makers by incorporating artificial intelligence tools and technologies such as knowledge bases, natural language, genetic algorithms, multi-agent systems, fuzzy logic, and neural networks.

SMEs play a crucial role in the Indian economy, contributing significantly to employment generation, exports, and GDP. The growth and development of SMEs in India are influenced by factors such as the implementation of a green organizational culture, formalization of human resource management practices, access to finance, and succession planning. Improving formalization of human resource management can enhance productivity and performance, while access to affordable credit and financial services is critical for SMEs' growth and development.

Artificial intelligence (AI) has the potential to replace human intelligence in various aspects of life, including service industries, business decision-making, and human resources. AI offers advantages such as automation, competitive edge, sustainability, research and development, personalized recommendation, continuous learning, lack of bias, scalability, enhanced customer experience, and resource allocation. However, it also introduces challenges related to human-AI interaction, bias mitigation, and ethical considerations.

AI has the potential to revolutionize various aspects of life, including business, but further exploration and understanding of its dynamics and potential impacts are needed.

Artificial intelligence (AI) offers numerous advantages in business decision-making, including personalized recommendations, continuous learning, reducing bias, scalability, and improving customer experience. However, AI also has disadvantages such as lack of transparency, potential bias, errors or malfunctions, implementation costs, emotional loss, security and privacy concerns, job replacement, and lack of creativity and innovation.

Transparency is crucial for individuals to understand how decisions are being made and have recourse against system outcomes. AI systems can perpetuate and amplify existing biases, leading to unfair outcomes. To address these issues, businesses should implement regulatory frameworks that require transparency mechanisms and develop AI systems that are unbiased and transparent.

Bias is another significant disadvantage of AI in decision-making, as it increases the risk of unintended and harmful behavior from poor design or implementation. Research efforts have focused on AI safety, identifying and addressing specific problems related to accident risk.

Implementation challenges include the need for appropriate infrastructure, data management, governance, and ethical considerations. Emotional intelligence is essential for decision-making, but AI systems lack it, limiting their ability to consider the emotional impact of decisions.

Security and privacy issues are significant disadvantages of using AI for decision-making in business. Businesses should invest in necessary infrastructure, prioritize data management and governance, and establish clear ethical guidelines and frameworks.

AI can lead to job replacement, which can affect employees' responses to AI job replacement. To mitigate these negative consequences, businesses should provide opportunities for upskilling and reskilling employees, foster a supportive organizational culture, and address job insecurity.

Intelligent Decision Support Systems (IDSS) are advanced AI-based decision support systems that aid decision-makers in complex problem-solving scenarios. These systems integrate knowledge reasoning, model calculations, and data analysis to offer decision support. They have evolved from traditional frameworks to more advanced systems based on AI and data warehouses. In the medical sector, IDSSs transform raw medical data into sophisticated algorithms, facilitating clinical decision-making processes. In the financial sector, IDSS has played a pivotal role in harnessing artificial intelligence for activities such as financial processing and economic management.

The architecture of expert systems is crucial in the design and development of IDSS, with methodologies like backward chaining and forward chaining being utilized to enhance system performance. Evaluation frameworks have been established to ensure the effectiveness of IDSS systems, and evolutionary-based optimization techniques have been explored to enhance the intelligence and adaptability of decision support systems within enterprises.

Data mining techniques, such as association rule learning, classification, clustering, and regression, have significantly improved the capabilities of IDSS by extracting valuable insights from vast datasets. These techniques enable the discovery of hidden patterns and relationships within data, facilitating an inductive approach to data analysis and enhancing decision support capabilities.

Decision trees and fuzzy logic are key components of IDSS, offering structured and intuitive approaches to decision-making processes. Case-based reasoning is another key component, enabling decision-makers to make informed decisions based on the complexity of the situation. Bayesian Networks (BNs) are a probabilistic framework for modeling complex relationships and making informed decisions based on uncertainty and incomplete information. Multicriteria Decision Analysis (MCDA) is a crucial methodology in IDSS, providing a structured approach to decision-making when multiple objectives need to be considered.

The adoption of technology by small and medium-sized enterprises (SMEs) is influenced by various technological factors within the Technology-Organization-Environment (TOE) framework. Complexity, which refers to the perceived difficulty or intricacy of implementing and using the technology, can pose challenges for SMEs with limited resources and technical expertise. Technological competence, which refers to the internal IT infrastructure and existing IT skills within the organization, can be related to complexity. Compatibility is another significant factor in the adoption of recent technology by SMEs. Research findings reveal that compatibility has a significant effect on social media adoption by SMEs. When the technology is perceived as compatible with the organization's operations, it is more likely to be adopted.

Relative advantage is a significant factor in the adoption of recent technology by SMEs. It refers to the perceived superiority of new technology over existing alternatives. Research has shown that when the economic and financial advantages associated with green practices are well understood, SMEs are more likely to adopt them. Additionally, top management support is essential for creating a supportive climate and providing adequate resources for technology adoption, helping to overcome barriers and resistance to change within the organization.

Technology readiness is a critical factor in the adoption of recent technologies by SMEs. This readiness encompasses various dimensions, including technological, organizational, environmental, and managerial factors. Government policies also play a significant role in the adoption of recent technology by SMEs. Stakeholder influence plays a significant role in motivating SMEs to adopt digital media for stakeholder engagement, Building Information Modeling (BIM) adoption in SMEs in China, and the adoption of social media by SMEs.

Competitive pressure and supplier efficacy play crucial roles in the adoption of new technologies and practices by SMEs. Understanding and addressing these factors is crucial for SMEs to effectively adopt and leverage new technologies.

The integration of Intelligent Decision Support Systems (IDSS) in organizations is a promising way to enhance decision-making processes. However, there is a significant gap in understanding the factors influencing IDSS adoption within organizations due to the complexity and volume of data in modern enterprises, exponential growth of data, and cognitive biases. The Technology-Organization-Environment (TOE) framework is a valuable theoretical model for understanding technology adoption and implementation within organizations. Quantitative data collection methods are essential for conducting rigorous and systematic research across diverse disciplines.

The Indian Micro, Small, and Medium Enterprises (MSME) sector is a significant indicator of the country's economic landscape, contributing to inclusive growth and employment generation. A diverse sample of 508 participants was selected using appropriate sampling techniques, including simple random sampling, stratified random sampling, and cluster sampling. The data collection procedure involved a multi-faceted approach, including simple random sampling, online and offline methods, a network of networks, and snowball sampling techniques.

Structural Equation Modeling (SEM) was used as a statistical technique to explore and validate complex relationships among variables by analyzing both observed and latent variables. This approach offers flexibility and power in analyzing data across various fields, making it a valuable method for researchers seeking to unravel complex relationships within their datasets.

The discussion chapter of a thesis on the factors influencing the adoption of intelligent decision support systems highlights the importance of understanding both complexity and environmental factors. Complexity factors include issues such as malfunctions, artificial intelligence bias, human emotion disadvantages, security and privacy issues, job replacement concerns, the complexity of adoption, artificial intelligence self-learning capabilities, and employee non-cooperation. These factors can significantly hinder the successful implementation of intelligent decision support systems within organizations.

Malfunctions in the system can lead to distrust among users and stakeholders, affecting the overall adoption rate. Issues related to bias in artificial intelligence algorithms can result in unfair decision-making processes, further complicating adoption efforts. Human emotion disadvantages and job replacement concerns may lead to resistance from employees who fear being replaced by automated systems, impacting the organizational culture negatively. Security and privacy issues pose a significant threat, especially in industries dealing with sensitive data.

The complexity of adoption itself, including the integration of new technologies and processes, can be a barrier that organizations need to navigate. The self-learning aspect of artificial intelligence introduces a level of unpredictability that organizations must manage effectively. Employee non-cooperation can arise due to a lack of understanding or training, emphasizing the importance of change management strategies in the adoption process.

Environmental factors also play a pivotal role in shaping the adoption landscape of intelligent decision support systems. Influences from competitors, pressures to adopt new technologies, the need for business stakeholder approval, and customer demands can all impact the decision-making process within organizations.

By understanding and addressing the challenges posed by complexity and environmental factors in the adoption of intelligent decision support systems, organizations can unlock opportunities for growth, innovation, and sustainable development. Through strategic planning, stakeholder engagement, and continuous learning, the potential benefits of these systems can be fully realized across various sectors, ultimately driving progress and success in the digital era.

6.2 Implication

The adoption of Intelligent Decision Support Systems (IDSS) has significant implications across various sectors, including organizations, industries, governments, and academia. In organizations, the integration of IDSS can transform decision-making processes, leading to improved operational efficiency, strategic planning, and competitive advantage (Baldin et al., 2021). However, this adoption journey is accompanied by challenges such as addressing malfunctions and biases in artificial intelligence algorithms, ensuring data security and privacy, managing job replacement concerns, and handling the complexity of adoption and change management (Tan & Teo, 2000). To overcome these challenges, organizations should implement robust error detection mechanisms, prioritize data security measures, maintain transparent communication with employees, and invest in comprehensive training programs to equip staff with the necessary skills to effectively utilize IDSS (Wijnhoven, 2021).

In industries, the adoption of IDSS can have a substantial impact on competitiveness, innovation, and market dynamics (Kamar, 2021). By utilizing advanced analytics and predictive modeling capabilities, organizations can gain deeper insights into consumer behavior, market trends, and competitive positioning. However, industry players must navigate challenges such as regulatory compliance, ethical considerations, and economic disruptions resulting from the widespread adoption of IDSS (Nie & Fan, 2021). Proactive experimentation, innovation, and adherence to ethical guidelines are essential for organizations to differentiate themselves in the market, comply with regulations, and achieve sustainable growth (Zou & Khern-am-nuai, 2022).

Governments play a crucial role in shaping the adoption landscape of IDSS through regulatory frameworks, policy initiatives, and investment incentives (Chhajer, 2022). By aligning regulatory mandates with technological advancements, governments can create an environment conducive to IDSS adoption while addressing concerns related to data security, privacy, and ethical considerations. Policy frameworks, regulatory oversight, and investments in research and development are vital for governments to promote the responsible and ethical deployment of IDSS across different sectors (Zhao & Saeed, 2022). Furthermore, leveraging IDSS in public service delivery and governance can optimize resource allocation, enhance decision-making processes, and improve citizen engagement and participation (Fernandes et al., 2015).

In academia, researchers and scholars contribute to the advancement of IDSS through interdisciplinary research, education, and knowledge dissemination (Mohy-eddine et al., 2023). By exploring the complexities and challenges associated with IDSS adoption, academics identify best practices, lessons learned, and emerging trends that inform industry practices and policy development. Education and training initiatives are critical in preparing the next generation of professionals to effectively harness the full potential of IDSS (Venkatesh et al., 2013). Interdisciplinary collaboration among academia, industry, and government facilitates knowledge exchange, drives innovation, and addresses complex challenges in the field of IDSS (Alzahrani et al., 2017).

In conclusion, the adoption of Intelligent Decision Support Systems presents a transformative opportunity for stakeholders across various sectors. By addressing the unique challenges and opportunities linked to IDSS adoption, organizations, industries, governments, and academia can unlock the full potential of data-driven decision-making and drive positive outcomes for societal, economic, and educational advancement. Through collaborative efforts and proactive engagement, stakeholders can navigate the complexities of IDSS adoption, harness technological capabilities, and create a more resilient, equitable, and sustainable future for all.

6.3 Future research

When the result of an SEM analysis indicates a not so perfect fit between the proposed model and the data, it suggests that the hypothesized relationships among the variables do not adequately explain the observed data patterns. In such cases, researchers need to reconsider their model specifications and data collection strategies to improve the model fit. One potential approach for future research to enhance model fit is to explore the use of different data sources or collection methods that may better capture the underlying relationships among the variables of interest.

1. Investigating the determinants of adoption of Intelligent Decision Support Systems (IDSS) using several models: Studies in this field can explore the various complex elements that impact the acceptance and use of Intelligent Decision Support Systems (IDSS). Researchers can acquire a better understanding of the decision-making processes involved in the adoption of IDSS in many areas by using different models such as expert systems, fuzzy logic, decision trees, and Bayesian models. Through the process of comparing and contrasting these models, the research can reveal the key aspects that have a significant impact on the adoption process and how they interact in various organisational contexts.

2. Incorporating Additional Technology Adoption Models into the Study: Researchers can expand the scope of their study by including other technology adoption models, such as TAM (Technology Acceptance Model) and UTAUT (Unified Theory of Acceptance and Use of Technology), instead of solely focusing on IDSS. By integrating the knowledge gained from these models with the aspects that are unique to the adoption of Integrated Decision Support Systems (IDSS), researchers can enhance their understanding of the dynamics involved in the adoption process. This includes examining how perceived usefulness, ease of use, and social factors impact the decision-making process.

3. Sampling from Heterogeneous Populations: In order to enhance the applicability of the results, future studies should go beyond a single country, such as India, and include samples from diverse populations, including both large corporations and small and medium-sized enterprises (SMEs) from different countries. Through comparative analyses, researchers can determine how cultural, economic, and institutional factors impact the adoption of IDSS in various national contexts. This technique can provide useful insights into the debate between the universal and context-specific factors that determine the adoption of IDSS.

4. Embracing Qualitative Analysis for Enhanced Understanding: Although quantitative methods provide valuable statistical insights, qualitative analysis can provide a more

profound comprehension of the intricacies and difficulties associated with the deployment of IDSS. Subsequent investigations can utilise qualitative approaches, such as interviews, focus groups, and case studies, to investigate the subjective experiences, perspectives, and decision-making processes of stakeholders engaged in the implementation of IDSS. Researchers can enhance the comprehensive understanding of IDSS adoption phenomena by combining qualitative findings with quantitative data, so enriching the scope and depth of their analysis.

6.4 Conclusion

The present study has shed light on the complex obstacles that small and medium-sized firms (SMEs) in India encounter when attempting to implement Intelligent Decision Support Systems (IDSS). By using a thorough survey approach and careful structural equation modelling, we have determined the environmental and essential complexity elements that obstruct this process. Significant complexity factors are the integration challenges and the innate technological sophistication of IDSS. These problems highlight the need for SMEs to build strong internal capacities and strategic planning in order to handle the complexities of IDSS implementation.

However, the adoption landscape is further complicated by external factors including inconsistent vendor support and strict regulatory frameworks. These outside factors emphasise how crucial it is for SMEs to actively participate in regulatory frameworks and cultivate a solid rapport with technology providers in order to obtain the resources and assistance required for an IDSS adoption to be effective.

The study's conclusions offer practical advice for small and medium-sized enterprises (SMEs), highlighting the necessity of funding skill-building and training programmes, strategic planning for system integration, looking into low-cost alternatives, and proactive regulatory involvement. Furthermore, the study emphasises how important strong vendor relationships are to overcome support-related obstacles.

In the end, this study adds to our understanding of the IDSS adoption process among Indian SMEs by providing a useful framework for both theoretical research and real-world implementation. SMEs can fully leverage the revolutionary potential of intelligent decision support systems, spurring innovation and growth in a more competitive and complicated market context, by recognising and tackling the fundamental obstacles that impede IDSS adoption.

APPENDIX A

SURVEY COVER LETTER

Dear Participant,

Thank you very much for your participation in my research study on "INTELLIGENT DECISION SUPPORT SYSTEM - FACTORS OF ADOPTION USING TOE FRAMEWORK BY SMALL AND MEDIUM ENTERPRISES IN INDIA". This survey is part of same research study. Information collected through this survey will be used strictly for academic purposes and confidentiality of responses will be maintained.

Thank you very much for sparing your precious time.

Best Regards

Basheer Khan

Swiss School of Business and Management

APPENDIX B
SURVEY GUIDE

1. Will you adopt this product?
2. Turnover of your organization
3. Age
4. Gender
5. Marital status
6. Your highest educational qualification.
7. What kind of incorporation is your company
8. Your Experience in SME sector in years.
9. Industry
10. No. of Employees
11. Do you feel this technology will enable Improved Decision Quality?
12. Do you feel this technology will enable Faster Decision-Making
13. Do you feel this technology will enable Enhanced Strategic Planning.
14. Do you feel this technology will enable Risk Assessment and Mitigation
15. Do you feel this technology will enable Cost Reduction
16. Do you feel this technology will enable Scalability
17. Do you feel this technology will enable Real-Time Monitoring
18. Do you feel this technology will enable Competitive Advantage
19. Do you feel that technology will have bias in AI decision-making?
20. Do you feel that technology will have errors or malfunctions in AI systems?
21. Do you feel that technology implementation of AI systems in business decision-making can be costly and resource-intensive?
22. Do you feel that technology will lack human emotion advantage?
23. Do you feel that technology will have security and privacy?
24. Do you feel that technology will result in job replacement?
25. How is the complexity of adoption?
26. How comfortable are you letting the computer learn on its own?
27. Do you feel employees will be hesitant to be part of the technology due to privacy issues?
28. Do you perceive any risks associated with this product?
29. Do you feel that decision making has become complex?
30. Do you feel the current technology that you already have is sufficient for you to take decisions?
31. Do you feel the need to upgrade to this technology?
32. How will you rate the accuracy and reliability of the product?
33. How user friendly will the product be?
34. Would you like to use this product as a tool or as a replacement of man?
35. What kind of decision maker are you?
36. Do you use any kind of technology to make decisions?
37. Is your company dependent on employee's feedback?
38. Are you concerned with the affordability of the technology?
39. Are you aware of such technology?
40. Are you threatened that technology will replace you?
41. Are you comfortable that it will replace your manager, resulting in a cost advantage?

42. How likely are you to like the product?
43. How likely are you require this product in current times?
44. How useful will this product be?
45. Are you willing to be?
46. Has your organization done any innovation in the past?
47. Do you support technology innovation in your organization?
48. Is it suitable to your kind of organization?
49. Are you willing to share your data with the database warehouse?
50. Do you feel your business lacks something to adopt this technology?
51. Do you feel that this technology will fill the gap in decision making?
52. Do you feel your industry requires this product?
53. How government support will aid adoption?
54. Do you feel that this technology has to be regularized?
55. Do you think ethics and privacy will play a major role in adoption?
56. Do you feel that your competitors will influence your adoption of this technology?
57. Do you feel you will be forced to adopt this technology sooner or later?
58. Do you feel supplierâ€™s technical knowledge is vital for adoption?
59. Do you feel business stakeholders will facilitate its use?
60. Will customer influence or impact be essential in adopting this technology?

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