A STUDY ON THE PERCEPTION OF MARKETING MANAGERS IN EMPLOYING ARTIFICIAL INTELLIGENCE FOR SALES AND MARKETING

By

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ABSTRACT

"A Study on the Perception of Marketing Managers in Employing Artificial Intelligence for Sales and Marketing"

This study examines the issues swaying marketing managers' behavioral intention to adopt artificial intelligence (AI) in sales and marketing. Through a comprehensive investigation, the study identified performance expectancy, effort expectancy, and peer influence as the key predictors affecting marketing managers' intentions to use AI-driven tools. The research also considered individual, organizational, and technological factors that could influence these predictors.

The findings suggest that organizations should focus on addressing these factors to facilitate successful AI adoption in sales and marketing. This includes providing training and education, ensuring management support, fostering a culture of innovation, and implementing effective change management strategies. Additionally, organizations should invest in developing user-friendly, reliable, compatible, and customizable AI tools, while ensuring robust data management practices.

The study provides valuable insights for organizations seeking to harness the power of AI to transform their marketing and sales processes. By understanding the factors influencing marketing managers' intentions and addressing the identified challenges, organizations can successfully integrate AI, stay competitive, and achieve better results in an increasingly dynamic and data-driven marketplace. Future research could explore additional factors, the actual implementation process, and measurable outcomes of AI adoption in sales and marketing to provide more comprehensive and actionable insights.

KEYWORDS

- Customer Relationship Management (CRM)
- Data Analytics (DA)
- Go to Market (GTM)
- KPI (Key Performance Indicators)
- S & M (Sales & Marketing)

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Chapter 1: Introduction

The history of Artificial Intelligence in “sales and marketing” is a narrative of progressive integration and innovation. It began in the mid to late 20th century when computers and databases started to be used for managing customer relationships and segmenting markets. This was essentially the dawn of CRM (Customer Relationship Management) systems, which could be considered a rudimentary form of AI as they automated tasks that were previously performed manually.

The arrival of the Internet and digital technology in the late 1990s and early 2000s heralded a new era for AI in sales and marketing. Online platforms began to collect vast amounts of data about consumer behavior, creating an opportunity for more advanced analytics. For example, Amazon launched its recommendation engine in 1998, which used collaborative filtering, an early form of AI, to suggest products “based on a customer's browsing history and purchase behavior”.

The breakthrough for “Artificial Intelligence in sales and marketing”, however, came with the advent of ML, a subdivision of Artificial Intelligence, in the 2010s. Machine learning enabled computers to learn from data, identify patterns, and make predictions, leading to major advancements in personalized marketing, lead scoring, and sales forecasting. At the same time, the explosion of big data offered machine learning algorithms vast amounts of information to learn from, further enhancing their capabilities.

In current years, we understood the rise of even more sophisticated Artificial Intelligence tools in sales and marketing, including chatbots, virtual assistants, and AI-powered content creation and curation tools. These tools use natural language processing, another subset of AI, to interrelate “with customers in a human-like way”, offering personalized customer service and product recommendations.

Despite the rapid advancements of the past few decades, the history of AI in sales and marketing is still being written. With the ongoing developments in AI technology, “we can expect to see even more innovative applications in the future”.

1.1.Applications of AI in Sales and Marketing

Sales and marketing have traditionally been human-centered activities, relying on human intuition, relationships, and understanding. But the advent of artificial intelligence (AI) is revolutionizing these fields, optimizing the existing processes and bringing about unprecedented changes.

1.1.1. Personalized Customer Experiences:

Personalization is a key application of AI in sales and marketing, transforming how companies interact with their customers. According to Accenture, “91% of consumers are more likely to shop with brands who recognize, remember, and provide relevant offers and recommendations” (Accenture, 2018). AI algorithms play a vivacious role in allowing this level of personalization.

Artificial Intelligence’s power to investigate huge volumes of information, including “customers' browsing history, purchase history”, and other behaviors, allows companies to craft highly detailed profiles of each customer (Chaffey and Ellis-Chadwick, 2019). This data analysis capacity is something humans cannot replicate at the same scale and speed. The AI's customer profile then becomes the basis for personalization strategies.

These strategies can take many forms. For instance, Amazon uses AI “to provide personalized product recommendations based on each customer's browsing and” purchasing history (Nguyen et al., 2020). Similarly, Netflix uses AI to tailor its content recommendations to each user's viewing habits (Gomez-Uribe and Hunt, 2016). This AI-driven personalization makes customers feel understood and valued, leading to improved customer reliability and eventually, augmented trades. Besides, personalization extends beyond product recommendations and can also be used in targeted advertising. Google, for example, uses AI to analyze users' search histories and online behavior to serve highly relevant ads (Perelló-March et al., 2020). Furthermore, personalization can also be instrumental in email marketing campaigns, where AI can be used to tailor subject lines, content, and send times to individual recipients, which can significantly improve open and conversion rates (Resnick and Harte, 2020).

In conclusion, AI enables a level of personalization in sales and marketing that was unimaginable a few years ago. By offering customers highly personalized and relevant experiences, businesses can significantly enhance customer loyalty and profitability.

1.1.2. Improved Sales Forecasting:

Sales forecasting is a critical activity in any organization, as it influences numerous strategic decisions such as resource allocation, budgeting, and inventory management. Traditionally, sales forecasting has been a complex and often inaccurate process due to various uncertain factors. However, the advent of AI has significantly improved the accuracy and efficiency of sales forecasting (Fildes and Goodwin, 2007).

AI algorithms can analyze vast quantities of historical data, including previous sales, market trends, and customer behavior, to predict future sales with remarkable precision. The use of AI in sales forecasting eliminates a significant amount of guesswork and allows businesses to make more informed, data-driven decisions (Liu et al., 2018).

ML, a subsection of AI, has been particularly influential in improving sales forecasting. It enables algorithms “to learn from the data and improve their predictions over time”. For example, ML models “can identify complex patterns and trends in sales data that might be” difficult for a human analyst to spot (Bandara et al., 2020). Moreover, AI can handle and “analyze unstructured data, such as social media posts or customer reviews”, to gain insights that can inform sales predictions. Sentiment analysis, powered by natural language processing (another branch of AI), can interpret and quantify these sentiments to further refine sales forecasts (Medhat et al., 2014). Additional hopeful AI application in sales predicting is deep learning, which utilizes neural networks to analyze data and make predictions. These deep learning models have shown great promise in their ability to handle large, complex datasets and make accurate predictions (Baldi and Sadowski, 2014). In summary, AI technologies, particularly “machine learning and deep learning, have significantly improved the accuracy of” sales forecasting, enabling businesses to make more informed strategic decisions.

1.1.3. Efficient Lead Scoring:

Lead scoring is a crucial aspect of the sales process, enabling companies to rank potential customers based on their likelihood to convert. Traditionally, this process relied heavily on the salesperson's intuition and experience, often resulting in a subjective and inconsistent process (Johnston and Marshall, 2016). However, the application of AI has revolutionized lead scoring, making it more objective, efficient, and accurate.

Lead scoring traditionally depends on salespeople's intuition and experience, making it inherently subjective and inconsistent. AI can systematize this process by analyzing vast amounts of data about leads and assigning each a score based on their likelihood to convert. Not only does this make the process more objective, but it can also identify promising leads that human salespeople might overlook.

AI-driven lead scoring systems use advanced algorithms to analyze vast amounts of data about potential customers, assigning each a score based on their likelihood to convert (Olenski, 2017). This data can include demographic information, browsing history, interaction with marketing content, and more. These algorithms can process data at a scale and speed that humans cannot match, enabling them to identify promising leads that salespeople might overlook (Mintz, 2018).

ML, a subclass of Artificial Intelligence, plays a significant role in modern lead scoring. “Machine learning algorithms learn from historical data, identifying patterns” and correlations that can predict a lead's likelihood to convert (Zheng et al., 2020). For example, if the data shows that leads who interact with a certain type of content are more likely to convert, the algorithm will give a higher score to leads who show similar behavior.

Predictive analytics is another key aspect of AI-driven lead scoring. “Predictive analytics uses historical and current data to forecast future outcomes”, providing sales teams with a more accurate estimate of the potential revenue from each lead (Shmueli et al., 2019).

By automating the lead scoring process and making it more objective and data-driven, AI allows “sales teams to focus their efforts on the most promising leads”, improving efficiency and potentially increasing conversion rates. However, it's worth noting that AI “does not eliminate the need for human judgment in sales.” Instead, it enhances it by providing valuable data-based insights that salespeople can use to inform their strategies.

1.1.4. Chatbots and Virtual Assistants:

Artificial Intelligence -“powered chatbots and virtual assistants are becoming increasingly” sophisticated, capable of handling a wide range of customer inquiries and issues. These tools can provide 24/7 customer support, freeing up human staff for more complex tasks. Moreover, they can use data about each interaction to continuously learn and improve, providing an ever-improving customer experience.

The use of Artificial Intelligence ‘in sale and marketing’ has been broad and transformative, “with chatbots and virtual assistants being one of the most” visible manifestations of this technology. These AI-powered tools are capable of simulating human-like interactions, offering customer service, product recommendations, and even engaging in sales conversations (Vandeventer et al., 2019).

“One of the most significant benefits of AI-powered chatbots” and virtual assistants is their “ability to provide 24/7 customer support. Unlike human agents’, these AI tools able to operate around the 24/7, responding to customer inquiries instantly, regardless of the time of day (Lu et al., 2019). This constant availability significantly improves customer service, enhancing “customer satisfaction and loyalty.”

Moreover, Artificial Intelligence -“powered chatbots and virtual assistants” able to handle a high volume of interactions simultaneously, which “would be impossible for human agents. This capacity allows businesses to” scale their customer service efforts efficiently, without a proportional increase in staffing costs (Vandeventer et al., 2019).

Importantly, AI chatbots and virtual assistants are not merely reactive but can learn from each interaction to continuously improve their performance. They “use machine learning algorithms to analyze data” from past interactions and improve their responses over time. For example, if a chatbot's response to a specific query often leads to customer dissatisfaction, the algorithm can adjust the chatbot's future responses to similar queries (Kumar et al., 2020).

Furthermore, virtual assistants “can be integrated into various platforms, including websites, social media”, and even messaging apps, to engage customers where they are most comfortable (Sheth, 2020).

In conclusion, AI-powered chatbots and virtual assistants are a powerful tool for enhancing customer service in sales and marketing. By providing fast, personalized, and round-the-clock customer support, these tools can significantly “improve customer satisfaction and loyalty, leading to higher sales and profitability”.

1.1.5. Advanced Analytics:

Marketing strategies are only as good as the insights that drive them. AI can “sift through massive amounts of data to uncover trends, correlations, and insights that might otherwise go unnoticed”. It can also conduct sentiment analysis on social media and other online platforms, giving businesses a better understanding of how their brand is perceived and what their customers want.

“Advanced analytics is an umbrella term” that encompasses a variety of AI-powered techniques used to analyze data and generate insights. These techniques, which include “predictive analytics, data mining, big data analytics, and machine learning, are playing an increasingly important role in sales and marketing” (Chen et al., 2012).

The advent of AI has ushered in a new era in advanced analytics, enabling companies to process vast quantities of data in real time, “identify patterns and trends, predict future outcomes, and make more informed decisions” (Kumar and Reinartz, 2012).

Predictive analytics, for instance, uses statistical algorithms and “machine learning to identify patterns in historical and current data”, enabling the forecasting of future events. This capability can be particularly valuable in sales forecasting, customer segmentation, and personalized marketing (Shmueli et al., 2019).

Data mining is another crucial aspect of advanced analytics. Data mining involves exploring and “analyzing large amounts of data to discover meaningful patterns and rules”. These insights shall be applied to inform strategic decisions, such as product development, marketing strategies, and customer retention efforts (Han et al., 2011).

Big data analytics focuses on processing and analyzing vast datasets that traditional data processing applications cannot handle. These datasets can include transaction data, customer feedback, “social media data”, and more. “The insights derived from big data analytics can inform a wide range of strategic decisions”, from pricing strategies to new product development (Chen et al., 2014).

Furthermore, “machine learning, a subset of AI, enables algorithms to learn from data” and improve over time, leading to increasingly accurate predictions and insights. Machine learning can be applied in many areas of sales and marketing, including lead scoring, customer segmentation, and personalized marketing (Kelleher et al., 2015).

In conclusion, advanced analytics powered by AI has greatly enhanced the ability of sales and marketing teams to “analyze data and generate valuable insights. By leveraging these insights, businesses can make more informed decisions”, leading to increased sales and profitability.

1.1.6. Content Creation and Curation:

AI can also assist in creating and curating content for marketing campaigns. It can analyze what types of content resonate best with a company's target audience and then generate similar content or suggest content to be shared. While AI cannot entirely replace human creativity, it can augment it and take care of routine tasks, freeing humans to focus on strategy and ideation.

In the realm of sales and marketing, AI has increasingly become an integral component in content creation and curation. With its ability to analyze large datasets and understand complex patterns, “Artificial Intelligence has the potential to significantly enhance the quality and relevance of content for customers” (Järvinen and Taiminen, 2016).

AI-powered content creation involves the use of AI algorithms, particularly natural language generation (NLG), to generate text-based content such as product descriptions, blog posts, and even news articles. NLG uses structured data as input to create human-like text that is both coherent and contextually relevant (Gatt and Krahmer, 2018).

AI can also be utilized to create personalized content. By analyzing a user's browsing history, preferences, and previous interactions, AI can create content tailored to each user's specific interests and needs. This personalized approach can significantly improve customer engagement and conversion rates (Li and Karahanna, 2015).

Content curation, on the other hand, involves using AI to select and present existing content that is relevant to a particular audience or individual. This process is vital in a digital landscape where customers are often overwhelmed by the amount of available content. Through content curation, AI can help businesses provide their customers with a more focused and relevant content experience (Rathore et al., 2020).

An excellent example of AI-powered content curation is recommendation systems, as seen on platforms like Netflix and Amazon. “These systems use machine learning algorithms to analyze a user's past behavior and suggest content or products they might like”. This personalized approach can enhance the customer experience, increase engagement, and drive sales (Zhang and Chen, 2019). The integration of AI in content creation and curation has proved instrumental in tailoring “the content experience to the needs and preferences of the individual user, leading to increased engagement and higher conversion rates”.

AI's potential in sales and marketing is vast. It's more than just a tool; it's a transformative force that is redefining these fields from the ground up. “It's important to remember, however, that AI is not meant to replace human intelligence” and creativity but rather to augment them. The most successful businesses in the age of AI will be those that strike the “right balance between human and artificial intelligence, leveraging the strengths of each to create a whole that is greater than the sum of its parts”.

1.2 Research Problem

The emergence of artificial intelligence (AI) has transformed various industry sectors, and sales and marketing are no exceptions. AI's potential to revolutionize these fields is recognized globally, offering capabilities to automate and streamline processes, predict consumer behavior, personalize customer experiences, and optimize marketing strategies. Despite the potential benefits, some studies suggest that companies have been slow to adopt AI in their marketing strategies. The apprehension is often attributed to factors such as lack of technical expertise, concerns about data privacy, perceived financial implications, or simply a lack of understanding of AI's potential applications and benefits.

However, empirical data on this phenomenon, particularly from the perspective of marketing managers, is still limited. There is a lack of comprehensive research exploring why marketing managers may be reluctant to employ AI in sales and marketing operations. What are their perceptions about AI? Do they recognize its potential in enhancing marketing effectiveness? What barriers or challenges do they foresee or experience in adopting AI?

The gap in understanding these perceptions presents “the research problem that this study aims to address: "What are the perceptions of marketing managers in employing artificial intelligence for sales and marketing”, and what factors influence their willingness or reluctance to adopt AI in their marketing strategies?" By studying this problem, this research will not only contribute to the academic field but also provide valuable insights for organizations, technology developers, and policymakers aiming to accelerate AI's integration in the sales and marketing sectors.

1.3 Purpose of Research

“The purpose of this research study is to delve into the mindset of marketing managers regarding the employment of Artificial Intelligence (AI) in sales and marketing”. The study seeks to uncover and understand their attitudes towards the effectiveness of AI tools, and how these attitudes are shaped by a range of factors. “The intention is to shed light on the internal and external drivers and barriers that influence the adoption of AI technology in their marketing strategies”.

Specifically, the research aims to accomplish three main objectives. “The first objective is to understand the marketing managers' attitudes towards the effectiveness of using AI for sales and marketing”. This includes their perceptions of AI's ability to enhance efficiency, streamline processes, and improve marketing outcomes.

The second objective is to identify the factors affecting marketing managers' behavioural intentions towards using AI for sales and marketing. This will involve an exploration of a “variety of factors, including but not limited to technical expertise”, resources, perceived cost, and the perceived complexity of AI technologies.

Lastly, “the third objective is to analyse the perceived impact of using” Artificial Intelligence for sales and marketing from the perspective of marketing managers. This involves assessing their expectations and experiences concerning AI's influence on business performance, customer engagement, competitive advantage, and other related aspects.

Significance of the Study

The accelerating advancement of artificial intelligence (AI) technologies and their increasing penetration into various industry sectors underscore the need for understanding their implications on business processes, specifically in the area of sales and marketing. AI offers transformative capabilities in the form of predictive analytics, customer segmentation, personalized advertising, and more, allowing for a potentially significant enhancement in marketing effectiveness. Yet, the level of AI adoption in marketing remains varied across businesses. An exploration into the factors influencing this phenomenon, especially from the perspective of marketing managers who often make decisions about technology adoption, remains critical.

This study is imperative as it would provide comprehensive insights into the “perceptions of marketing managers regarding the use of AI in their respective fields”. While there's ample research on the technical aspects of AI and its potential for businesses, there's a relative dearth of empirical studies exploring the human aspect, particularly the attitudes, concerns, and expectations of the professionals expected to use these technologies. Understanding these can help businesses address potential barriers and create a more conducive environment for technology adoption.

Moreover, “the findings of this research could potentially guide companies in identifying the possible obstacles preventing or slowing down the adoption” of AI in their marketing efforts. By understanding what influences marketing managers' attitudes and behavioral intentions, businesses can tailor their strategies accordingly, providing necessary resources and support to facilitate AI integration. This can potentially lead to improved marketing outcomes and overall business performance.

Additionally, this study is essential for technology developers and policymakers. Insight into the experiences and expectations of marketing managers can inform the development of more user-friendly AI tools, more effective training programs, and more inclusive policies that address potential concerns and barriers, including those related to privacy and ethics.

Finally, the research also adds to the academic discourse on AI's role in transforming business processes. The findings can further enrich the theoretical frameworks and empirical knowledge on technology adoption in the context of sales and marketing, offering directions for future research. Therefore, the need for conducting this study is justified on multiple grounds: practical implications for businesses and technology developers, policy-related insights, and academic contributions.

1.5 Research Purpose and Questions

“The purpose of this research is to gain a comprehensive understanding of marketing managers' perceptions and attitudes towards the employment of Artificial Intelligence (AI) in sales and marketing”. This involves exploring their viewpoint on the effectiveness of AI, identifying factors that influence their behavioral intentions towards adopting AI, and assessing their perceptions of the impact of AI usage in their business practices. The research will contribute valuable insights for businesses, technology developers, and policy-makers, helping them better facilitate AI adoption in sales and marketing.
“To achieve the aim of the study, the following research questions were framed”.

1. What are the attitudes of marketing managers towards the effectiveness of using AI in sales and marketing?

This question aims to uncover marketing managers' perceptions about the potential and actual effectiveness of AI applications in their field. This includes understanding their views on the ability of AI to improve efficiency, productivity, customer engagement, and other key marketing outcomes.

2. What factors influence marketing managers' behavioural intentions towards using AI for sales and marketing?

This question intends to identify both the barriers and motivators that affect marketing managers' decisions to adopt AI in their strategies. Factors may range from technical expertise, perceived complexity of AI technologies, resources, perceived cost, to organizational culture and support.

3. How do marketing managers perceive the impact of using AI for sales and marketing on their business performance?

“This question is designed to analyze the perceived consequences of AI adoption from the perspective of marketing managers”. It seeks to understand how they perceive AI's influence on various aspects such as business performance, competitive advantage, customer engagement, and overall marketing effectiveness.

Chapter 2: Literature Review

2.1 History of AI

Artificial Intelligence (AI), since its formal introduction in the mid-twentieth century, has become an interdisciplinary field, transforming various sectors from healthcare to business. Artificial Intelligence (AI), a term coined by John McCarthy, is commonly traced back to its inception in the Dartmouth Conference of 1956 (McCorduck, 2004). This seminal conference gathered many of the day's leading researchers in fields like mathematics, engineering, and cognitive science, setting the foundation for future AI research. Prior to this, however, the groundwork was being laid by other influential thinkers and scientists.

Perhaps the most noteworthy among them was British mathematician Alan Turing. Turing proposed a fundamental question in his 1950 paper, "Can machines think?" which sparked a philosophical and scientific debate that continues to this day (Copeland, 2000). To answer this, he conceptualized the 'Turing Test,' a thought experiment designed to gauge a machine's ability to exhibit intelligent behaviour equivalent to, or indistinguishable from, that of a human. The Turing Test, despite its criticisms and limitations, has played a crucial role in shaping the course of AI research.

During the 1960s, the first AI systems were developed with a focus on problem-solving. Two notable systems include the 'Logic Theorist' and 'General Problem Solver' developed by Newell and Simon (1972). The Logic Theorist, often referred to as the "first artificial intelligence program," was capable of proving mathematical theorems by representing them as logical statements. The General Problem Solver, on the other hand, was designed to imitate human problem-solving techniques and was used as a tool for understanding human cognition. These systems marked a significant shift in AI research, leading to the development of problem-solving using heuristic methods, which are rule-of-thumb strategies derived from experience.

Despite the significant progress, the AI research of the 1950s and 1960s was primarily symbolic AI or "good old-fashioned artificial intelligence" (GOFAI), focusing on high-level symbol manipulation rather than learning from data (McCorduck, 2004). These early systems were limited by the available computational power and the lack of sufficient data. Nonetheless, they laid the groundwork for future AI models and algorithms, setting the stage for the subsequent progress in the field.

The late 1970s and 1980s, termed the 'AI winter,' represented a challenging period for AI research. The hype and overly optimistic predictions about AI's capabilities, coupled with technical limitations, led to disillusionment and subsequent funding cuts (Nof, 2019). AI's lofty promises of creating general artificial intelligence were not yet fulfilled, leading to a lack of faith in the field's potential.

Nevertheless, despite the financial and perceptual challenges, the AI winter witnessed the emergence of some notable AI systems. For instance, expert systems like MYCIN and DENDRAL, albeit limited in their capabilities, showed a significant potential for AI in specialized fields such as medicine and chemistry (Buchanan, 2005). MYCIN was designed to diagnose bacterial infections and recommend antibiotics, while DENDRAL was an AI program used for inferring molecular structures. Despite their limitations, these expert systems demonstrated AI's potential usefulness in solving complex real-world problems, fostering further research in AI's applied domains.

By the 1990s, there was a resurgence in AI research interest, fueled primarily by a shift in approach towards machine learning. Machine learning is an AI approach based on the premise that systems can learn from data, identify patterns, and make decisions with minimal human intervention. This marked a significant departure from earlier AI methodologies that were largely based on pre-programmed rules (Jordan and Mitchell, 2015).

One of the prominent applications of machine learning in this period was the development of IBM's Deep Blue, a chess-playing computer. In 1997, Deep Blue famously beat the reigning world chess champion, Garry Kasparov, marking a symbolic milestone in AI's progress (Campbell et al., 2002). This event signalled the end of the AI winter, leading to renewed interest and substantial investments in the field.

The turn of the 21st century marked a significant shift in the AI landscape with the advent of advanced machine learning techniques, particularly deep learning. Deep learning is a subset of machine learning inspired by the structure and function of the brain's neural networks. It utilizes multiple layers of artificial neural networks to model high-level abstractions in data, proving exceptionally effective in tasks such as image and speech recognition (LeCun et al., 2015).

The resurgence of neural networks, which were conceptually introduced in the 1960s, can be attributed to the advent of powerful computational capabilities and the availability of vast amounts of data. These advancements made it feasible to train larger, deeper networks, thereby significantly improving their performance (Goodfellow et al., 2016).

One of the most notable deep learning architectures is the Convolutional Neural Network (CNN), which has revolutionized the field of computer vision. Yann LeCun, Yoshua Bengio, and others have significantly contributed to the development and popularization of CNNs, which are capable of effectively recognizing patterns in images, thereby facilitating tasks such as object detection and facial recognition (LeCun et al., 2015).

Similarly, Recurrent Neural Networks (RNNs), especially the Long Short-Term Memory (LSTM) variant, have made significant impacts on natural language processing and speech recognition. RNNs and LSTMs have the unique ability to process sequential data, making them ideal for tasks involving language and time-series data (Hochreiter and Schmidhuber, 1997).

In recent years, large-scale language models, such as GPT-3, developed by OpenAI, have showcased the power of advanced machine learning and deep learning techniques. GPT-3, with its 175 billion parameters, can generate coherent and contextually relevant text, thereby demonstrating proficiency in tasks ranging from translation to content creation (Brown et al., 2020).

Despite the remarkable progress, there are still considerable challenges to overcome. These include making AI models more efficient, reducing their reliance on large datasets, improving their interpretability, and ensuring ethical usage.

The rapid progress and pervasiveness of AI have raised a host of ethical and societal concerns that necessitate careful attention. These issues are multifaceted, ranging from personal privacy to larger societal impacts.

One of the critical issues is privacy, which has come under threat with the increasing use of AI and data-centric technologies. AI systems, especially those utilizing machine learning, often require vast amounts of data to function effectively. This data often includes personal and sensitive information, raising concerns about data misuse, security breaches, and violations of privacy (Bellovin et al., 2020).

Bias in AI is another significant issue, stemming from the fact that AI systems learn from the data they are trained on. If this data reflects societal biases, AI systems may inadvertently perpetuate or even amplify these biases. Numerous studies and real-world examples have demonstrated how AI systems, including those used in critical domains like hiring and judicial decision making, can be biased against certain demographic groups (Barocas and Selbst, 2016).

Moreover, the increasing autonomy of AI systems has led to concerns about accountability and decision-making. As AI systems become more capable and autonomous, it becomes challenging to determine who is responsible when these systems make errors or cause harm (Hellström, 2013). This concern is especially relevant in areas like autonomous vehicles and AI in healthcare, where AI decisions can have severe consequences.

Finally, the concept of 'Explainable AI' or 'XAI' has gained attention, particularly in relation to deep learning models. Despite their effectiveness, these models are often referred to as 'black boxes' due to their opacity; it's challenging to understand why they make the decisions they do (Adadi and Berrada, 2018). This lack of transparency can be problematic, especially in domains where understanding the reasoning behind decisions is critical, like in healthcare or legal settings.

In conclusion, as AI continues to progress and become increasingly embedded in our society, it is crucial to address these ethical and societal concerns. Developing guidelines and regulations, promoting transparency, and including diverse perspectives in AI development are among the steps that could help ensure AI benefits all of society while minimizing potential harms.

Artificial intelligence (AI) systems, made up of a blend of hardware and software components, are increasingly used in marketing due to their ability to process and analyze data, understand environmental variables, and inform decision-making and action-taking processes (European Commission, 2018). Even though a lot of focus has been on AI's online advantages, the acceptance of AI in e-commerce by consumers has been overlooked. According to utility theory, such modern technologies allow consumers to easily identify and choose the best product options, thus reducing search time and cost (Collins, et al., 2021). The conception of AI has a long-standing history, traced back to ancient Greece, covering a broad range of areas including science and philosophy. Its present form owes much to Alan Turing and the pivotal 1956 Dartmouth College conference, where John McCarthy officially introduced and defined the term "Artificial Intelligence," an event often called "the birth of artificial intelligence" (Russell and Norvig, 2020).

Research suggests that technological advancements in applications such as AI, Augmented Reality (AR), and Virtual Reality (VR) offer highly personalized experiences that impact consumer choices and behaviors (Huang and Rust, 2017; Pantano and Pizzi, 2020). AR applications, for example, enhance consumer perceptions of utility and pleasure (Nikhashemi et al., 2021), foster positive attitudes (Yaoyuneyong et al., 2016; Wedel et al., 2020), and boost purchase intentions and word-of-mouth (Yaoyuneyong et al., 2016). Similarly, VR applications evoke positive emotional responses towards a brand by stimulating powerful sensory impressions, such as the feeling of tangibility through haptic feedback (Wedel et al., 2020). The VR/AR app market is one of the fastest-growing sectors of software development globally (Unity Apps, 2021), but the effects of technological advancements in apps on consumer experiences remain underexplored. This gap in knowledge might be due to outdated theoretical foundations, thereby calling for future research that leverages novel theoretical frameworks such as physical and psychological continuity theory, teletransportation theory, and service prototyping theory (Lacewing, 2010; Langford and Ramachandran, 2013; Razek et al., 2018).

Certain experiences facilitated by AI can be positive and memorable, while others may not meet customer expectations. Automated messaging services utilized by service organizations can offer convenience but may also lead to limited customization, causing potential customer dissatisfaction. However, clients with high emotional intelligence may be more receptive to AI services. It's also important to note that the delivery of services isn't always gratifying for the service providers. Certain attributes related to brand behavior and attitude can significantly influence consumer loyalty (Joshi, Chirputkar, & Jog, 2015). The study suggests that customer satisfaction is a complex construct influenced by various elements like brand selection, consumer and distributor perceptions, marketing strategies, service quality, and delivery.

Balakrishnan et al. (2009) suggested 'address mapping' as a cost-effective method for businesses to geo-locate IP addresses and find mobile phones. Using Foursquare as an example, they showcased that despite early location cheating attacks, solutions like the cheater code, which verifies device location via GPS, can be effective. In the era of the "bring your own device" (BYOD) model, mobile device management (MDM) solutions like SOTI or Airwatch are essential. These solutions create a safe environment for running enterprise applications, enabling administrators to set compliance requirements, remotely wipe data, and oversee device operations. As part of a comprehensive mobile security strategy, all MDM solutions generally include data encryption, certificate support, and robust authentication methods.

The contemporary consumer market is fiercely competitive, making customer retention an essential focus for service companies in the coming years (Appiah-Adu, 1999). Consumer retention is especially vital given that businesses consider consumers as a valuable asset, and many companies are suffering significant losses in their consumer base (Swanson and Hsu, 2009). With the mobile phone market undergoing substantial changes and heightened competition globally and domestically, customer retention (CR) has become a significant issue in this sector.

Despite implementing various relationship marketing strategies (Gronroos, 1995; Ravald and Gronroos, 1996; Ranaweera and Prabhu, 2003), many mobile phone companies are witnessing a depletion in their current customer bases, often exceeding a rate of thirty per cent. Andic (2006) found that major UK mobile network operators such as Orange, T-Mobile, O2, and Vodafone, lose over a third of their young customers, under the age of 25, to competitors. Most managers are unable to deal with this reality, despite trying to comprehend the reasons behind this significant loss (Reichheld, 1996). These losses can lead to reduced sales, profits and, eventually, the downfall of a business (Reichheld and Sasser, 1990; Reichheld and Kenny, 1990). The difference in the rates of customer acquisition and retention in the mobile industry has led to the exploration of customer retention from different perspectives, including economic, behavioural, and psychological standpoints. However, most past research hasn't provided a compelling theoretical justification or practical explanation for customer's repeat purchase behaviour.

Hall (2019) described AI marketing as the application of technology for enhancing the customer experience. The entry of technologies, especially AI, has influenced the role of marketing managers. With a more thorough understanding of customers, companies can make better decisions about the direction of their business. AI helps companies to get this crucial insight into their customers.

Schrage and Kiron (2018) conducted a global executive study, revealing that 79% of the responding CEOs believed in investing in the skills and training of their marketing professionals to enhance machine learning (ML) effectiveness in marketing. It's commonly believed that AI's rise in marketing, particularly CRM, will cause significant job losses. Despite this, the United States Bureau of Labor Statistics (2020) projects a 6% growth in the employment of advertising, promotions, and marketing managers from 2019 to 2029. In contrast to the common belief that AI can replace human intuition and creative abilities, it's critical to understand how the roles of marketing managers are changing with the increase in tools that support and automate marketing decisions (Dawar, 2020).

AI initially focused on high-level cognition that encompasses multi-step reasoning, understanding natural language, innovative artifact design, novel plan generation to achieve goals, and self-reasoning (Langley, 2011). Known as strong AI (Kurzweil, 2005), this approach focused on symbolic reasoning, but the progress was slow and led to its abandonment by many AI disciplines.

Kaka et al. (2019) noted that India, being the country with the most publicly traded companies globally, offers vast growth opportunities for both local and foreign businesses. This growth is driven by the Indian Government's "Make in India" initiative promoting digital technology. The growing demand for 4G/5G technology to power various applications like "audio-video streaming, navigation, music downloads, gaming, e-commerce, postal solutions, video chat boxes, and social networking" is evident in both urban and rural areas. However, the requirement for lower-cost technology is more pronounced in rural areas. With fierce competition among telecom companies following the entry of Reliance JIO with its unlimited phone and data usage offers, other telecom service providers like Airtel, Vodafone Idea, and BSNL have had to slash their prices to retain and acquire new customers.

Bedi and Surbhi (2017) highlighted the significant challenges, uncertainties, and numerous concerns that need to be addressed during a company's pre-merger and post-merger stages. As a result of mergers and acquisitions, customers have become wary of procuring new services from the consolidated company, inadvertently aiding the growth of the competitor's customer base. The study examines the impact of trust dynamics following mergers and acquisitions, and the importance of integration planning in the Indian telecom industry. These factors either contribute to the success of a merger and positively affect customers, the market, and the company, or they cause the merger's failure. Azam, Qiang, and Abdullah (2012) stated, "customer satisfaction is not only a key performance outcome in online retail buying but is also a significant predictor of customer online shopping and purchase intention". The authors identified certain factors affecting customers' online purchasing decisions, including customer satisfaction with the system, service interfaces, security, relevance, consistency, understandability, navigability, and telepresence. Premkumar and Rajan (2012) determined that mobile number portability is a crucial factor affecting customer retention in the Indian mobile telecom market. It poses a significant challenge for the country's mobile telecom service providers. The study also showed that customer satisfaction is paramount when it comes to retaining customers. In the Indian mobile telecom market, customer retention decreases as customer satisfaction increases. However, customer satisfaction is influenced by two factors: customer trust and service quality.

Artificial intelligence (AI) has the potential to influence revenue by trillions of dollars in the coming decade. It is disrupting many industries by significantly impacting a broad spectrum of business processes. Never before have so many businesses planned or invested in AI technology, and it has also garnered immense interest from regular investors and venture capitalists. However, AI remains a complex technology with various sub-concepts and intricate algorithms, accompanied by serious ethical considerations.

Makridakis (2017) divided the various perspectives on AI in the current market into four categories: optimists, pessimists, pragmatists, and sceptics. Herding behaviour, the act of blindly following trends and decisions made by others, is prevalent, especially in cases where market buzz and competitive pressures force decisions despite a lack of understanding. This behaviour is especially common in the IT sector, where managers are known to follow each other blindly when making IT investment decisions (Kauffman & Li, 2003). While not all herding negatively impacts the industry, it can affect a single company's expectations of a potentially beneficial technology.

Ding and Li (2019) found significant signs of herding behaviour in both the consumption of digital books and making website purchases. Similarly, new bidders on eBay tend to flock to existing bids (Simonsohn & Ariely, 2008). To date, no studies have explored the link between AI and herding behaviour. Therefore, it was necessary to measure the impact of any herding phenomenon on AI technology, analyse what factors triggered the herding, and determine the effects on the overall AI industry.

Gacanin and Wagner (2019) described the challenges that need to be overcome to implement autonomous customer experience management (CEM). The paper also discussed how AI and machine learning were used to create a crucial business value driver and an intelligence network. An AI-powered chatbot equipped with natural language processing (NLP) can help improve the overall customer experience (Nguyen and Sidorova, 2018). AI and ML algorithms enable efficient data processing, allowing the best decisions to be made (Maxwell et al., 2011). AI is necessary to analyse customer routines, purchases, preferences, and more (Chatterjee et al., 2019). Artificial Intelligence User Interface (AIUI) has been shown to benefit Customer Relationship Management (CRM) functions (Seranmadevi & Kumar, 2019). Through the use of AI and IoT, traditional retail stores are transformed into smart retail establishments, improving the customer experience and strengthening the supply chain (Sha & Rajeswari, 2019).

Promotion management is evolving from traditional methods to digital and physical ones due to the global digital transformation. AI enables personalization and customization of messages based on individual customers' preferences and profiles (Huang & Rust, 2020). Emotional AI algorithms allow real-time tracking of individual customers' likes and dislikes. Using netnography to analyse the content of social media platforms offers new opportunities for marketers to align their marketing strategies with customers' preferences (Tripathi & Verma, 2018).

Gray (2018) discussed the challenges with AI systems in his article titled “AI can be a troublesome teammate”. He believes that AI lacks certain human qualities like mutual concern, a shared sense of vulnerability, and faith in competence, making it untrustworthy. However, he also acknowledged that AI has proven to be useful in areas such as weather forecasting (Wirtz et al., 2018).

Whang, Ren, and Lu (2018) delved into the realm of artificial intelligence in the telecommunications industry with a focus on customer service systems. Their research, "Key technologies of AI in customer service systems", concluded that AI offers a cost-effective and highly efficient alternative to traditional, human-operated customer service. Nevertheless, they identified certain shortcomings in the AI technologies of the time, such as lack of flexibility and an impersonal tone. Despite higher levels of automation within organisations, they observed no proportional increase in successful outcomes, and the customer experience notably declined. Ra'ed (2012) supported the connection between customer satisfaction and long-term customer retention, revealing the positive impact of call centre services on customer satisfaction and retention within the Indian telecom sector.

As ecommerce becomes more prevalent, live chat has emerged as a popular tool for real-time customer assistance. In recent years, advances in AI technology have led to a shift from human-operated chat services to conversational software agents, or chatbots (Gnewuch et al., 2017; Pavlikova et al., 2003; Pfeuffer et al., 2019a). Although AI-powered chatbots offer a more accessible customer service avenue, missteps such as inappropriate responses can lead to mismatches between user expectations and system performance. Consequently, this could result in negative customer experiences and user noncompliance.

The design of chatbots is crucial in establishing a sense of social presence (Rafaeli and Noy, 2005; Derrick et al., 2011; Zhang et al., 2012; and Elkins et al. 2012). Most prior research concentrated on the effects of anthropomorphic design signals on human perceptions and adoption. Yet, this focus has mainly been on embodied conversational agents, leaving disembodied chatbots, which primarily communicate through text, less explored. Recently, conversational computing platforms, such as IBM Watson Assistant, have allowed the development of advanced chatbots capable of empathetic interaction, offering a more human-like communication experience.

As chatbots increasingly take over customer service, the efficacy of persuasion and compliance strategies in technology-based self-service contexts also comes into question. One such strategy is the continued-question method, a technique used to secure user compliance.

Balancing service efficiency and quality presents a major challenge for customer service providers. The use of CAs promises to enhance service quality and interactions while offering cost-saving opportunities. They are capable of handling a large volume of routine inquiries, freeing up human agents for other tasks. According to estimates, CAs could lead to significant reductions in global customer support expenditures (Reddy, 2017b; Techlabs, 2017). Despite these benefits, the lack of personalized attention in purely self-service channels could negatively impact sales (Raymond, 2001). Therefore, a gradual transition to AI-based customer service is recommended, especially at the beginning of customer relationships.

By mimicking social actors, CAs can shape service encounters and execute tasks previously managed by human service staff. They provide 24/7 availability, a critical feature for customers seeking immediate assistance. As CAs become more sophisticated, they are increasingly able to exhibit human traits such as friendliness, leading to a more personalized and engaging service experience.

The increasing prominence of chatbots across digital platforms is undeniable, with their numbers surging significantly within a few years. For instance, Facebook Messenger's chatbot count spiked from 11,000 in 2016 to 300,000 by 2019. Despite their growing use, the infancy of these AI-powered chatbots has been linked to significant failure rates and a lack of user trust. Studies show a noticeable discrepancy in the nature and quality of human-chatbot interactions compared to human-human conversations. Users tend to use more profanity and have longer interactions with chatbots, which could negatively impact the effectiveness of chatbot's suggestions and thereby question the benefits of this self-service technology. Consequently, understanding how chatbot design influences user cooperation becomes essential.

Social Response Theory suggests that people automatically apply social norms to computers designed with human-like characteristics, a phenomenon known as anthropomorphism. Humans instinctively assign human traits and behaviors to non-human entities to understand them better. This leads to the Computer as Social Actors (CASA) phenomenon where users interact with anthropomorphized computer systems similarly as they would with other humans. Thus, even a small amount of anthropomorphic cues can trigger social responses, following the same social dynamics as human-human interaction. For instance, people apply racial and gender stereotypes, flattery effects, and personality responses when interacting with machines.

Verbal anthropomorphic design cues (ADCs), like speech, aim to evoke the illusion of intelligence in a non-human entity, while non-verbal ADCs, such as physical appearance, encourage social bonding by adopting human features. However, chatbots, which primarily operate through text-based dialogue, lack dynamic and physical representations. They are mostly disembodied and use verbal and non-verbal cues such as language style and blinking dots to interact with users. While a handful of studies have focused on verbal ADCs, the majority has centered on embodied agents.

Compliance, in the context of human-chatbot interactions, refers to the user's acquiescence to a request made by the chatbot. Various compliance techniques have been studied, with one key approach being the Foot-in-the-Door (FITD) technique. This involves making small requests to users which, when accepted, lead to larger requests. For instance, in online marketing, small commitments like submitting an email address or clicking a link are followed by more substantial requests aiming to increase conversions. Users are more likely to agree to smaller requests due to the lower cognitive effort involved, and once they commit to a minor request, they tend to agree to larger ones later to maintain consistency in their behavior.

The desire for consistent behavior is rooted in psychological processes such as self-perception theory and commitment-consistency theory. These theories suggest that people form their attitudes through self-observation, leading to a bias towards accepting future requests of the same nature after accepting an initial request. Consumer behavior studies have shown that the need for self-consistency influences purchasing decisions. Thus, understanding these aspects of human psychology is crucial for optimizing chatbot design and interaction.

Conversational AI and chatbots are increasingly becoming integral components of online business and client support. Consistency in these interactions is essential, as studies have shown that individuals tend to be more compliant when they feel a sense of relationship building (Cialdini and Trost, 1998). Even brief exposure to a request from a familiar individual can enhance the likelihood of compliance (Burger et al., 2001). Personal motives such as guilt alleviation, earning favor, or improving self-esteem may also influence compliance (Whatley et al., 1999).

During the COVID-19 pandemic, it was observed that AI chatbots were rapidly replacing human-operated call centers due to workforce limitations (Hao, 2020). This led to a notable surge in the use of IBM's Watson Assistant by 40% between February and April 2020. Furthermore, in rural India, mobile phones play a crucial role in providing information and maintaining communication channels, which is significantly influencing the socioeconomic fabric (Mehta, 2013).

Schrotenboer (2019) highlighted the impact of AI on the customer journey in both online and physical retail environments. The fusion of AI technologies in these spaces is closing the gap between brick-and-mortar and e-commerce experiences. AI advancements in recommendation systems and conversational interfaces are playing a crucial role in shaping customer experiences.

Bowen and Morsan (2018) discussed the application of AI and robotics in the service industry. The potential to use AI for harvesting valuable insights from vast customer data can significantly enhance personalization in service delivery. For instance, AI-driven cars can assist customers with their travel and hospitality needs, thereby improving the overall experience.

In their study on emotional intelligence, Salovey and Mayer (1990) emphasized the importance of recognizing, understanding, using, and managing emotions. Emotionally intelligent consumers can connect more deeply with employees, enhancing their service experience.

Prentice, Chen, & King (2013) found that emotional intelligence and job commitment can influence employee performance outcomes in customer-service contexts. They proposed a model (Three C Model of Confidence, Change, and Control) that encapsulates the impact of AI on institutions.

Pavaloiu (2016) explored how AI affects global trends, leading to shifts in external stimuli, marketing tactics, and management practices that influence consumer attitudes. Online retail giants like Amazon have leveraged AI to offer personalized shopping experiences (Smidt and Power, 2020), which has set new benchmarks for customer-centric services (Barmada, 2020). As AI continues to facilitate more personalized and efficient online shopping, it's reshaping business-customer relationships (Rust and Huang, 2014), with trust serving as the foundation for these technology-driven transformations (Pricewaterhouse, 2018).

Chatbots, as elucidated by Dempt (2016), start by examining the primary concepts and then further delve into the specifics. In response to a query, a chatbot will attempt to discern the central theme first, then utilize the 'funnel approach' to focus more intently on the issue. The system endeavors to interpret the user's input via rule-based and data-driven semantic techniques. The aim of rule-based methods is to automatically recognize data expressions. Data-driven methods work similarly to content analysis in qualitative social research, where categories are predetermined, and word use is coded into these categories to quickly assign related topics (Trendone, 2016).

According to Reeves and Nass (1996), users are more likely to trust a chatbot when it is presented as a team member rather than just a technological tool. When bots communicate in a style similar to their users, the information provided appears more credible. The chatbot should ideally present key information accurately and politely, making sure not to overload the user. Over time, the chatbot should learn about returning users based on past conversations and queries to enhance its service.

Service providers often offer customer care through various online channels, such as company websites, social media, emails, and chats, to improve service efficiency and engage customers effectively. Chat-based customer support is gaining prominence as it enables representatives to handle multiple queries simultaneously, proving to be a more resource-efficient method than email or phone assistance (Tezcan & Zhang, 2014).

In a study by Pretince and Nguyen (2020), they explored engaging customers through AI and employee service. The study involved a survey with customers in Australia who had used AI products and services, specifically in the hotel industry. The hotels used a range of AI tools, including chatbots, conversational robots, virtual assistance, voice-activated services, and travel experience enhancers. The study found that both employees and AI significantly influence customer engagement and loyalty.

Prentice (2013) noted that interacting with company service staff and AI services can sometimes be challenging due to the effects of moods and emotions on staff attitudes and behaviors. This, in turn, could negatively affect customer experience and perception (Neves and Eisenberger, 2012). However, customers with high emotional intelligence may expand their tolerance zones and empathize with staff, potentially accepting a lower level of service.

Loyalty, as defined by Oliver (1999), involves a deeply held commitment to consistently repurchase or repatronize a preferred product or service, leading to repetitive same-brand purchasing despite potential situational influences. Javalgi and Moberg (1997) have taken this a step further, defining loyalty from three different perspectives: behavioral, attitudinal, and decision-making.

Mobile marketing can help enhance customer satisfaction, strengthen customer-business relationships, and increase communication and interaction between customers and businesses (Anjorin and Amarsana, 2012). Galeano et al. (2016) noted that mobile marketing could affect a company's brand awareness, composition, and loyalty.

Mohannad, Daqar, & Smoudy (2019) studied the role of AI in enhancing the customer experience in several businesses in Palestine. They found a positive and significant relationship between AI and customer experience, with AI accounting for 26.4% of the variance in customer satisfaction. The research suggested that businesses should provide more personalized services to clients and use AI in call centers and after-sales support services to reduce customer waiting times.

In a study by Yau, Saad, and Chong (2021), titled "Leveraging Artificial Intelligence Marketing (AIM) to Enhance Customer Relationships", they developed a novel AIM model based on a wide array of existing literature. This model leverages big data and AI to generate insights and apply them to enhance customer relationships. The AIM model comprises three key components: a pre-processor, a main processor, and memory storage. With the use of AI, the main processor interprets structured data from the pre-processor, allowing for real-time decisions. They suggested the AIM framework offers several benefits like increased marketing efficiency, better decision-making, and more accurate predictions. Their study also identified areas for future research such as improving interpretability, understanding tacit and explicit knowledge, and exploring different ways to leverage consumer and market data.

Berry et al. (2006) found that AI-powered services can be classified as functional experiences in their study. However, Nanji (2019) noted that most users expressed dissatisfaction with AI services and preferred human interaction. This shows the need for further exploration of how customer interactions with AI and employee services can impact their relationship with a service organisation. Lemon and Verhoef (2010) emphasized the importance of customer engagement and loyalty in determining customer relationships, a topic further explored by Følstad, Nordheim and Bjørkli (2018).

In their study, titled "What Factors Influence User Trust in Customer Service Chatbots? An In-depth Interview Study", Følstad, Nordheim and Bjørkli (2018) looked into the aspects affecting users' trust in customer service chatbots through a series of interviews with 13 users. The findings suggested that users' trust in chatbots was influenced by the chatbot's understanding and response quality, the human-like nature of its self-presentation, and its professional appearance. They also noted the limitations of the study, including the small sample size and the limited market scope. Future studies, they suggest, should use larger sample sizes and include diverse marketplaces, and they also recommend using a theoretical framework to guide the research. Despite these limitations, the researchers have made strides in understanding factors that influence trust in customer service chatbots, and their findings will likely spur further research in this crucial area.

In a study conducted in 2021, Ameen and his colleagues explored how artificial intelligence (AI) is changing the dynamics of customer experiences in the retail sector. Their primary objective was to understand if integrating AI within consumer transactions could enhance overall customer interactions. To develop a theoretical model for their investigation, the researchers leaned on trust theory and service quality concept. Utilizing an online survey method, data was collected from consumers who used an AI-powered application to purchase beauty products. The insights from 434 responses revealed that the perception of sacrifice and trust played significant roles in modulating the effects of perceived convenience, customization, and AI-enabled service quality. It was also discovered that relationship commitment exerted a profound influence on AI-enabled customer experience. This pioneering research enriched the existing knowledge by underlining the mediating role of trust and perceived sacrifice in the context of AI-powered customer experiences.

In another vein, Brodie et al. (2011) among others, identified customer engagement as a co-creation process involving service providers and customers aimed at enhancing customer loyalty and procurement. This concept, due to its potential financial implications for both the customer and the organization, has gained popularity within the marketing literature. The existing body of research has, however, defined customer engagement in a variety of ways, creating some inconsistencies within the literature. For the purpose of this research, customer engagement was understood as a customer's emotional, cognitive, and behavioural investment in a company.

The incorporation of AI in marketing analytics can significantly improve customer satisfaction by determining the suitability of product designs in meeting customer needs (Dekimpe, 2020). Advanced AI capabilities such as topic modelling enhance service innovation and design, while preference weight measurements during product searches enable marketers to align strategies for better product management (Antons & Breidbach, 2018; Dzyabura & Hauser, 2019). Furthermore, deep learning technology provides personalised recommendations to customers, aiding in the exploration of new locations (Guo et al., 2018).

AI technology's capability to tailor services and products to meet specific customer needs is increasingly being harnessed by marketers. AI offers an invaluable opportunity for online retailers to analyze customer profiles and suggest personalised marketing offers. Additionally, AI enables constant, interactive engagement with customers and employees. For instance, a chatbot can efficiently handle frequently asked questions about products, their usage, and the purchasing process, enhancing customer satisfaction and engagement. Some of the most sophisticated strategies for improving overall customer experience leverage AI, data science, and emerging technologies.

According to a survey by Bain & Company, most businesses currently employ AI-powered tools to improve the customer experience and maintain a competitive edge. Further, research by Kim, Ferrin, and Rao (2008) has shown that customer trust positively impacts purchase intentions. Consequently, a customer's level of trust in an online retailer can directly affect their buying behaviour. Tech giants such as Amazon and Netflix are already leveraging AI to deliver targeted advertising, while smartphone manufacturers are incorporating dedicated AI processors into their devices to handle AI-based operations more efficiently.

Thatcher and colleagues (2013) delineated trust into two specific types: global and individual trust. The former pertains to customer perceptions and attitudes towards the e-commerce environment as a whole. The latter, on the other hand, is tied to individual experiences with specific online shopping platforms. Trust can be nurtured through interactive communication between the seller and the buyer, incorporating clear product descriptions and images to mitigate perceived risk. As suggested by Cătoiu et al. (2014), a strong negative correlation exists between perceived risks and trust.

An exploration into the effects of unfavorable online customer reviews on consumer product attitudes was carried out by Lee et al. (2008). They found that an abundance of negative online consumer reviews results in a conformity effect, implying that bad online evaluations may influence actual purchasing behavior or, at the very least, purchase intention. Gacanin and Wagner (2019) elucidated the challenges in implementing self-directed customer experience management (CEM). They further described how artificial intelligence and machine learning were utilized to create a sophisticated network that added significant economic value. Artificial intelligence-powered chatbots that used Natural Language Processing (NLP) enhanced customer service experience. The effective analysis of data through artificial intelligence and machine learning algorithms enabled the extraction of the most suitable conclusions.

Doorn et al. (2010) delved into a different perspective on the matter through their study, "Customer Engagement Behavior: Theoretical Foundations and Research Directions". Their research focused on understanding customer engagement from consumer, company, and context-based perspectives, presenting a comprehensive conceptual framework that identified its elements, precursors, and outcomes. They suggested that motivations rooted in the company were more enticing in promoting customer engagement by providing a pleasurable customer experience.

Ojapuska (2018) in his study, "The Impacts of Chatbots in Customer Engagement", emphasized the contemporary customer's demand for swift and personalized services that may or may not involve human interaction. The study also indicated how businesses are rapidly integrating chatbots to augment customer connection, engagement, purchasing processes, and automated resolution of recurring inquiries, thereby enhancing customer experience.

Brandtzaeg and Følstad (2017) delved into the usage of chatbots in their paper, "Why People Use Chatbots". They found that people use chatbots primarily due to their productivity; they facilitate easy access to information, expedite transactions, and are available round-the-clock. They concluded that consumers find interacting with chatbots amusing, and it has become a standard customer service approach, which summarizes the primary motivations driving organizations to employ chatbots to improve customer experience.

André et al. (2017) in their study, "Consumer Choice and Autonomy in the Age of Artificial Intelligence and Big Data", discussed how recent developments in AI-driven marketplaces and consumer micro-targeting have assisted in individualizing content recommendations for consumers, thereby making the choices more customized and easier to select from.

Zumstein and Hundertmark (2017) in their study, "Chatbots – An Interactive Technology for Personalized Communication, Transactions and Services", elaborated on how chatbots aid in providing personalized interaction with customers, allowing them to reach the company at any time and from any place.

Hancock et al. (2011) identified several elements that contribute to trust, which they categorized as human-related, robot-related, and environmental. Corritore et al. (2003) developed a widely accepted theory of trust in interactive systems, emphasizing users' trust in websites. Credibility, usability, and risk were recognized as crucial determinants of trust in this model. Trust in technology is a contentious concept (Fryer and Carpenter, 2006), but research on the topic is growing. For example, a review paper on robot trust outlined the main elements.

When developing strategies and planning marketing activities, marketers can benefit from using artificial intelligence to help with segmentation, targeting, and positioning (STP). In addition to STP, artificial intelligence can assist marketers in visualising the strategic orientation of the company (Huang & Rust, 2017). Text mining and machine learning algorithms have the potential to be utilised in a wide range of industries, including banking and finance, art marketing, retail, and tourism, in order to locate customer segments that are most likely to generate a profit (Dekimpe, 2020; Netzer et al., 2019; Pitt et al., 2020; Valls et al., 2018). The pool of customers that are targeted can be narrowed down even further by using a combination of data optimization techniques, machine learning, and causal forests (Chen et al., 2020; Simester et al., 2020).

Bloom's taxonomy of educational learning objectives was revised by Anderson and Krathwohl (2001) to place creation at the top of the hierarchy as the most important learning objective (Bloom et al., 1956). This was achieved through the revised version of Bloom's taxonomy that they created. They explain it as "putting elements together to form a coherent or functional whole; reorganizing elements into a new pattern or structure." "Putting elements together to form a coherent or functional whole." Bringing together disparate elements to form a whole that is either coherent or functional will demonstrate that the most significant factor that differentiates AI algorithms from conventional statistical methods is the idea of knowledge creation as it relates to Anderson's taxonomy. The authors argue that making such a distinction has significant implications for the likelihood of adopting AI technologies in aspects of marketing that require knowledge transfer or stand to benefit from it. Deep artificial neural networks are the primary focus of the vast majority of artificial intelligence applications in the business world. These networks are utilised to solve challenging predictive problems that were thought to be unsolvable in the past. Marketers can use predictive analytics to forecast future marketing actions and how those actions will impact behavior, generate insights to improve leads, acquire new customers, and achieve pricing optimization, among other things. They can also use predictive analytics to forecast how those actions will impact pricing (Murray & Wardley, 2014; Power, 2016). Researchers and managers in the field of marketing frequently establish objectives such as the maximisation of profit and market share, product cannibalization, customer retention, and utility maximisation (for examples, see Gonül and Hofstede, 2006; and Natter et al., 2007). Defining a holistic objective function is essential, however, because an AI algorithm is not restricted by common sense and does not have to operate within the confines of a predefined set of features or model specifications. This makes it possible for the algorithm to operate more freely.

The term "hassle-free service" refers to a service that is trouble-free, methodical, and problem-free, and in which the customers' demands are met without the presence of obstacles or confusion. Using blended artificial intelligence (AI), which is a combination of artificial intelligence and human intelligence, as well as data analytics, the articles by Görgens (2019) entitled “How can Artificial Intelligence use big data to form a better customer experience” and “Artificial Intelligence – Creating automated insights for customer relationship management.” AI (artificial intelligence) enables data analysis and individualised consumer experiences that would not be possible without machine learning's efficiency and efficacy. However, several earlier authors have noted a perceived lack of human touch, and additional investigation has revealed that data privacy is a big worry for customers. Clients are aware that businesses utilise their information to target them with customised advertisements. They do not, however, like to share their data with third parties and have little faith in organisations with regard to their information. As a result, Blended AI has been promoted as a panacea for all issues. Blended artificial intelligence is a synthesis of machine and human intellect. In the finalisation stage, an agent is utilised to conduct the final analysis of the data for clients. That way, organisations regain their human touch, communication is more transparent, and data is obtained with permission. As a result, data privacy could be restored. Consumer relationship management is critical for businesses, as the customer adds value to the corporation, whether economically or emotionally.

2.2 AI in Marketing

AI is becoming increasingly influential in decision-making, service provision, and creating strategic advantage for businesses. In this section, we synthesize empirical studies and scholarly discourses on AI's impact on business practices, technology adoption behavior, sustainable energy, and the evolution of marketing theory. Furthermore, we explore the associated ethical implications and the potential of AI in transforming the core of business functions. The rapid progress in AI has underscored the need for comprehensive reviews that consolidate the diverse findings and perspectives.

The study recognizes that AI has changed the way businesses interact with their clients, run their operations, and make decisions. Ahmad et al. (2021) and Luo et al. (2019) discuss how AI can enhance the sustainability of the energy industry and influence customer purchasing behavior, respectively. Similarly, Alt & Ibolya (2021) explore how AI can be utilized to identify potential users for banking chatbots based on technology adoption behavior. Balakrishnan & Dwivedi (2021) delve into the role of cognitive absorption in establishing user trust and enhancing experience. Additionally, Baabdullah et al. (2021) probe the impact of AI on SMEs and the consequences of AI-based B2B practices.

We also examine the practical applications of AI in several industries. For instance, Baldoni et al. (2020) highlight how AI can accelerate drug discovery, demonstrating the implications of AI for the biotechnology industry. On a different note, Carlson (2019) brings to light the concept of safe artificial general intelligence through distributed ledger technology.

Lastly, ethical considerations surrounding AI deployment are of significant importance and are studied by Dolganova (2021), who investigates how adherence to ethical principles can improve customer experience. Hickman & Petrin (2021) scrutinize trustworthy AI from a corporate governance standpoint. Together, these studies offer a rich tapestry of research that this review aims to consolidate and provide a comprehensive understanding of the impact, role, and ethical considerations of AI in business and society.

AI technology has proven to be effective in automating repetitive tasks and enhancing decision-making processes across diverse business functions. Alonso (2021) and Curry et al., (2021) discuss the significance of AI in big data innovation spaces, while Alt et al., (2021) and Sari et al., (2020) reveal the potential of AI-based chatbots in banking and other sectors. Also, AI has been shown to aid in predictive machine learning models based on an ethical taxonomy in university environments (Gallastegui & Forradellas, 2021).

Artificial intelligence (AI) is playing an increasingly influential role in the operations and processes of businesses across industries. AI applications extend across the spectrum of business operations, improving efficiency, enhancing decision-making capabilities, and transforming customer interactions.

AI technologies have been successful in automating routine tasks, reducing operational inefficiencies, and freeing up human resources for more strategic functions. Machine learning (ML) and robotic process automation (RPA) are increasingly being used to handle repetitive tasks such as data entry and analysis (Bughin et al., 2018). This has significant implications for businesses' operational efficiency and cost-effectiveness. As Bughin et al. (2018) highlight, companies can substantially improve their bottom line by deploying AI in these mundane areas of business operations.

Business process automation (BPA), powered by artificial intelligence (AI), is rapidly becoming a strategic enabler of business control and agility. It helps organizations streamline their processes, leading to improved efficiency, reduced error rates, and significant cost savings (Bughin et al., 2018).

AI-powered automation focuses on substituting manual effort in tasks that are highly repetitive and predictable. These tasks can range from data entry and invoice processing to more complex tasks such as customer support. A clear example is Robotic Process Automation (RPA), which uses AI and machine learning capabilities to handle high-volume, repetitive tasks that previously required humans to perform. RPA robots can capture data, run applications, trigger responses, and communicate with other systems just as humans do (Davenport & Ronanki, 2018).

Machine Learning (ML), a branch of AI, further enhances process automation by enabling systems to learn and improve from experience. ML algorithms can analyze large volumes of data and identify patterns that humans might miss. These algorithms then utilize this learned knowledge to automate decision-making processes and make predictions about future outcomes (Chui et al., 2018).

Automated business processes also extend to customer service with the advent of AI chatbots. Chatbots can handle simple queries, book appointments, and provide personalized recommendations, thus reducing the need for human intervention and improving customer experience (Huang & Rust, 2018).

Moreover, AI is transforming the field of supply chain management. Predictive analytics and machine learning are being used for demand forecasting, inventory management, and route optimization. This allows companies to anticipate customer demand more accurately, reduce operational costs, and improve delivery efficiency (Broussard, 2019).

Natural Language Processing (NLP), another application of AI, is being used to automate the analysis of textual data. This includes tasks such as sentiment analysis, language translation, and keyword extraction, which can provide valuable insights for decision-making (Bughin et al., 2018).

In conclusion, AI applications in business process automation are manifold and growing. From administrative tasks to customer service and supply chain management, AI is changing the way businesses operate, leading to increased efficiency and productivity. However, organizations need to carefully manage the transformation process to mitigate potential challenges related to technology integration, data privacy, and workforce training (Davenport & Ronanki, 2018).

Artificial Intelligence also aids in enhancing decision-making capabilities. Data analytics and machine learning provide valuable insights from the vast amounts of data businesses collect (Chui et al., 2018). By employing AI algorithms to analyze this data, companies can uncover patterns and insights that can guide strategic decisions (Chui et al., 2018). This application of AI empowers businesses to make data-driven decisions, reducing the reliance on intuition and increasing the likelihood of successful outcomes.

Artificial Intelligence (AI) has been a significant catalyst in enhancing decision-making processes across multiple industries. By enabling rapid processing and analysis of vast amounts of data, AI provides actionable insights that contribute to more accurate and informed decision-making (Brynjolfsson and McAfee, 2014).

AI-based predictive analytics plays a pivotal role in decision-making enhancement. Predictive analytics employs advanced AI and machine learning algorithms to identify patterns in historical and current data to forecast future outcomes. This can be applied in various domains, such as predicting customer behaviour in marketing, forecasting sales, anticipating maintenance needs in manufacturing, and predicting patient outcomes in healthcare. These predictions aid in strategic planning and risk mitigation, thereby leading to more informed decision-making (Siegel, 2016).

Predictive analytics is a branch of advanced analytics that uses a variety of techniques such as data mining, statistical algorithms, machine learning, and artificial intelligence to analyze current and historical facts, thereby making predictions about future or otherwise unknown events (Siegel, 2016). It's an aspect of data analytics that focuses on forecasting probable futures based on historical data.

The basic workflow of predictive analytics starts with collecting data. This data can be historical data, real-time data, or a combination of both. The collected data is then processed, cleaned, and organized for analysis. A statistical model is created based on the cleaned data. This model is then used to make predictions about future outcomes (Wang & Alexander, 2019).

The predictive model can employ a variety of techniques, including regression, classification, clustering, and time-series modelling. For example, regression techniques are used to predict a number, such as sales revenue, while classification techniques are used to predict a category, such as whether a customer will churn or not.

Predictive analytics has applications across various industries. In healthcare, it's used to predict the likelihood of certain diseases in patients. In finance, it's used to detect potential fraudulent transactions. In marketing, it's used to anticipate customer behavior and preferences to tailor offerings (Chen, Chiang & Storey, 2012).

Predictive analytics offers several benefits. It helps organizations forecast future trends, enabling them to plan and make strategic decisions. It also aids in identifying potential risks and opportunities. Moreover, predictive analytics can improve efficiency by streamlining operations and optimizing resources (Siegel, 2016).

Despite its benefits, predictive analytics does have some limitations. The quality of the predictions largely depends on the quality and quantity of the data used. Furthermore, developing an accurate predictive model requires technical expertise and significant computational resources. Additionally, predictive analytics can only forecast what might happen in the future; it cannot guarantee what will happen (Kuhn & Johnson, 2013). Thus, predictive analytics is a powerful tool for forecasting future outcomes based on historical and real-time data. It offers significant benefits but also poses some challenges. As such, organizations should consider these factors when implementing predictive analytics.

Prescriptive analytics, another facet of AI, goes a step further. It not only predicts future outcomes but also suggests various decision options to take advantage of the predictions. Prescriptive analytics uses complex algorithms and simulations to advise on possible outcomes. This ability to automate complex decisions can greatly enhance operational efficiency and business outcomes (Sharda, Delen & Turban, 2019).

Prescriptive analytics is the area of business analytics dedicated to finding the best course of action for a given situation. It is characterized by techniques such as graph analysis, simulation, complex event processing, neural networks, recommendation engines, heuristics, and machine learning (Powell & Mustafee, 2014).

The main goal of prescriptive analytics is to provide advice. It uses a combination of techniques and tools such as business rules, algorithms, machine learning and computational modelling procedures. These techniques are applied against input from many different data sets including historical and transactional data, real-time data feeds, and big data (García, Józefowska, & Sikora, 2019).

Prescriptive analytics not only anticipates what will happen and when it will happen, but also why it will happen. Further, prescriptive analytics suggests decision options on how to take advantage of a future opportunity or mitigate a future risk and shows the implication of each decision option. Prescriptive analytics can continually take in new data to re-predict and re-prescribe, thus automatically improving prediction accuracy and prescribing better decision options (García, Józefowska, & Sikora, 2019).

Prescriptive analytics is used in a variety of fields. For example, in healthcare, prescriptive analytics can be used to aid doctors in making diagnoses or recommending treatment options. In business, this kind of analytics can help organizations decide on the best course of action based on their data. This might include decisions about resource allocation, inventory management, and strategic planning (Lee & Siau, 2017).

One of the major benefits of prescriptive analytics is the ability to make informed decisions. By understanding the potential outcomes of various actions, decision-makers can select the best course of action. Furthermore, these decisions can be automated, leading to greater efficiency. Prescriptive analytics also enhances organizational agility, allowing businesses to respond to changes in their environment more effectively (Lee & Siau, 2017).

While prescriptive analytics provides numerous advantages, there are also several challenges. Creating accurate models can be difficult and time-consuming. Additionally, these models must be regularly updated as new data is obtained. This requires a significant investment of resources. There's also the risk of over-reliance on the prescriptive analytics system. Although the system can provide useful guidance, final decisions should always be made by human experts (García, Józefowska, & Sikora, 2019). Thus, prescriptive analytics is a powerful tool that uses a combination of data, algorithms, and machine learning to recommend the best course of action in any given situation. While it provides numerous benefits, it also poses some challenges that must be taken into consideration.

Decision Support Systems (DSS) are interactive software-based systems intended to help decision-makers compile useful information from raw data, documents, personal knowledge, and/or business models to identify and solve problems and make decisions. AI-enabled DSS have revolutionized decision-making by providing real-time insights and facilitating quicker, data-driven decisions. DSS are widely used in various domains like business intelligence, healthcare, and environmental management (Power, 2007).

Decision Support Systems (DSS) are a category of information systems that support business and organizational decision-making activities. They provide the necessary infrastructure for organizations seeking to extract actionable insights from raw data, and they offer the capacity to enhance the process of decision-making by providing reliable and timely information (Power, 2007).

Typically, a DSS will comprise four key components: a) Database: This is a collection of relevant data for a specific purpose. It can include historical records, real-time data, and large-scale datasets. b) Model: The model is the part of the DSS that processes the data and produces outputs in an understandable format. This can take the form of statistical models, algorithmic models, or even machine learning models. c) User interface: This is the platform through which users interact with the DSS. It must be designed to be user-friendly and intuitive, facilitating access to the system’s functionality. d) Knowledge-based component: Some DSS also include a knowledge-based component that utilizes artificial intelligence to aid in decision-making (Power, 2007).

There are several types of Decision Support Systems: a) Data-driven DSS: These systems emphasize access to and manipulation of large databases of structured data. b) Model-driven DSS: These systems emphasize access to and manipulation of a statistical, financial, optimization, or simulation model. c) Knowledge-driven DSS: These systems provide specialized problem-solving expertise stored as facts, rules, procedures, or in similar structures. d) Document-driven DSS: These systems manage, retrieve, and manipulate unstructured information in a variety of electronic formats (Shim et al., 2002).

The use of Decision Support Systems can bring numerous benefits to an organization, such as: a) Enhanced decision-making: DSS allow for quicker, more informed, and objective decisions by providing the decision-maker with improved access to pertinent information. b) Improved efficiency: By automating parts of the decision-making process, DSS can lead to increased productivity and efficiency. c) Increased competitive advantage: By harnessing data more effectively, companies can gain a competitive edge in their market (Power, 2007).

Despite their benefits, DSS can also present challenges: a) Implementation cost: The development and implementation of a DSS can be costly, both in terms of time and financial investment. b) Data quality: The effectiveness of a DSS is largely dependent on the quality of the data it uses. Poor quality data can lead to inaccurate or misleading results. c) User resistance: Like any change in organizational processes, the implementation of a DSS can meet resistance from staff members (Power, 2007). In conclusion, DSS offer a powerful way to harness data for decision-making purposes. While they do present certain challenges, the potential benefits make them an essential tool in modern business and organizational contexts.

Natural Language Processing (NLP) has emerged as a powerful tool in enhancing decision-making processes. It involves AI interpreting and manipulating human language to broaden the understanding of text-based data. NLP can extract insights from unstructured data, such as social media posts or customer reviews, that can inform strategic decisions. Sentiment analysis, a popular application of NLP, helps businesses understand customer sentiment towards their product or service, which can significantly influence decision-making (Hovy & Lavid, 2010).

Natural Language Processing (NLP) is a subfield of artificial intelligence (AI) that focuses on the interaction between computers and humans through natural language. The ultimate objective of NLP is to enable computers to understand, interpret, and generate human language in a valuable way (Liddy, 2001).

NLP can be broken down into two basic components: a) Natural Language Understanding (NLU): This involves the interpretation of human language by the machine. It allows the machine to understand the meaning and sentiment of the input it receives. b) Natural Language Generation (NLG): This is the process of generating meaningful phrases and sentences in human language from the data. It allows the machine to provide output in a way that is understandable to humans (Gupta, 2020).

Several techniques are commonly used in NLP, including: a) Tokenization: This is the process of breaking down text into words, phrases, symbols, or other meaningful elements (tokens). b) POS Tagging: Part-of-Speech tagging involves assigning grammatical properties (such as noun, verb, adjective) to each word in the text. c) Named Entity Recognition (NER): This technique is used to identify the named entities (like persons, places, organizations) in the text. d) Sentiment Analysis: This involves determining the attitude, opinions, and emotions of a speaker or a writer with respect to some topic. e) Machine Translation: This involves automatically translating text from one language to another. f) Speech Recognition: This involves converting spoken language into written form (Hirschberg and Manning, 2015).

NLP has found applications in numerous areas, including: a) Search Engines: NLP improves the efficiency of search engines like Google, Bing, and Yahoo. b) Voice Assistants: NLP is the foundation of voice-enabled assistants like Siri, Google Assistant, and Alexa. c) Sentiment Analysis: Businesses use NLP to understand customer sentiment towards products or services based on online reviews or comments. d) Machine Translation: Tools like Google Translate use NLP to provide translations between hundreds of languages. e) Text Summarization: NLP can be used to produce concise summaries of long documents or reports (Gupta, 2020).

Despite its advances, NLP faces several challenges: a) Ambiguity: Human language is full of ambiguity. Words often have multiple meanings, and sentences can often be interpreted in several ways. b) Lack of Structure: While some languages have a well-defined structure, many do not. This can make it difficult for NLP systems to accurately interpret and generate human language. c) Cultural Differences: Language use varies greatly between different cultures and communities, making it challenging to create NLP systems that can understand all the nuances and subtleties of human language (Hirschberg and Manning, 2015). In conclusion, while NLP presents significant challenges, it also offers immense opportunities. As AI continues to evolve, we can expect to see further advances in this fascinating field.

One of the most transformative effects of AI is in customer interactions and personalization. Through chatbots and other AI-powered tools, businesses can offer 24/7 customer service, handle customer queries more efficiently, and provide personalized recommendations (Huang & Rust, 2018). For instance, AI algorithms can analyze past customer behavior to provide targeted product suggestions, improving customer satisfaction and potentially increasing sales (Huang & Rust, 2018).

Artificial Intelligence (AI) has revolutionized the landscape of customer interaction and personalization in business. Through advancements in Natural Language Processing (NLP), Machine Learning (ML), and Predictive Analytics, companies are now capable of offering personalized experiences and engaging customers in more meaningful and productive ways (Huang and Rust, 2021).

AI enables businesses to tailor their services and products to meet the unique needs and preferences of each customer, thereby enhancing customer satisfaction and loyalty. This involves the use of Machine Learning algorithms to analyze large volumes of customer data, including transaction histories, browsing behavior, and social media interactions. From this data, patterns and trends can be identified, which can then be used to make personalized product recommendations, send targeted promotional messages, or provide customized content (Huang and Rust, 2021).

For instance, streaming services like Netflix and Spotify use AI algorithms to analyze users' viewing or listening habits and provide personalized recommendations. Similarly, e-commerce platforms like Amazon use AI to recommend products based on a customer's browsing and purchase history (Nguyen et al., 2019).

Personalization in business refers to the practice of crafting individualized experiences, communications, or products to enhance engagement with a customer or user. It is typically driven by the analysis and interpretation of data about the user, including their preferences, behavior, demographics, and interactions (Tam and Ho, 2005).

The advent of AI has taken personalization to the next level, as AI algorithms can process vast amounts of data quickly and accurately, thereby identifying patterns, predicting user behavior, and generating personalized recommendations or content (Huang and Rust, 2021). Here are some key aspects of personalization driven by AI:

In order to personalize experiences or communications, businesses must first understand who their customers are. This involves creating a user profile, which is a comprehensive picture of a customer's behaviors, preferences, and needs. User profiles can be built using both explicit data (information that users provide directly, such as age or location) and implicit data (information inferred from users' behavior, such as items they've viewed or purchased) (Li and Karahanna, 2015).

Recommendation systems are a common application of personalization, especially in the e-commerce and entertainment sectors. These systems use Machine Learning algorithms to analyze a user's behavior and preferences, and then suggest products, services, or content that the user might like. There are several types of recommendation systems, including collaborative filtering (which recommends items based on what similar users have liked) and content-based filtering (which recommends items similar to those the user has liked in the past) (Ricci et al., 2011).

Personalized marketing involves tailoring marketing messages and promotions to individual customers, based on their unique characteristics and behavior. This can include personalized email campaigns, targeted ads, or customized website content. AI can enhance personalized marketing by analyzing large datasets to identify patterns and predict customer behavior, enabling more accurate and timely targeting (Kumar et al., 2019).

Adaptive user interfaces adjust to the individual user's needs and preferences, providing a personalized user experience. This can involve changing the layout, navigation, or content of a website or app based on the user's behavior, device, or context. AI can facilitate adaptive user interfaces by learning from the user's behavior and continuously adjusting the interface to optimize the user experience (Findlater and Gajos, 2009).

Despite its potential benefits, personalization also presents several challenges. These include the need for large amounts of high-quality data, potential issues with user privacy and data security, and the risk of creating a "filter bubble" where users are only exposed to content that aligns with their existing preferences. Businesses need to carefully manage these challenges to effectively implement personalization (Huang and Rust, 2021).

AI has greatly enhanced customer interaction through technologies like chatbots and virtual assistants. Powered by NLP and ML, these tools can understand and respond to customer queries in natural language, provide information, and even handle simple transactions. This allows for 24/7 customer service, reduces response times, and frees up human agents to handle more complex issues (Xu et al., 2021).

Moreover, AI-powered sentiment analysis tools can analyze customer feedback, reviews, or social media posts to identify customer sentiment towards a product, service, or brand. This information can be used to address customer concerns promptly and improve the quality of products or services (Medhat et al., 2014).

By combining historical customer data with real-time behavioral data, AI systems can not only personalize the current customer experience but also predict future behavior and preferences. This predictive personalization can help businesses anticipate customer needs, offering products or services even before the customer realizes they need them. This not only enhances the customer experience but also provides opportunities for cross-selling and up-selling (Chen et al., 2012).

Despite the benefits, AI-driven customer interaction and personalization also present challenges. These include issues related to data privacy and security, potential biases in AI algorithms, and the risk of over-personalization, where customers may feel their privacy is being invaded.

As AI technologies continue to evolve, businesses will need to balance personalization with privacy, ensuring they use customer data responsibly. Moreover, they will need to focus on improving the transparency and fairness of AI algorithms, to ensure they deliver a truly personalized and inclusive customer experience (Huang and Rust, 2021).

Customer interaction involves any touchpoint or communication between a business and its customers. Traditionally, these interactions took place in person, over the phone, or via mail or email. However, the digital age has introduced a wealth of new channels for customer interaction, such as social media, live chat, mobile apps, and AI-driven technologies like chatbots and virtual assistants.

Customer interaction plays a crucial role in building relationships with customers, understanding their needs and expectations, and providing personalized service and support. Effective customer interaction can enhance customer satisfaction, loyalty, and advocacy, thereby driving business success (Singh and Sirdeshmukh, 2000).

Today's businesses aim to offer omnichannel experiences, where customers can interact with the business seamlessly across different channels (e.g., in-store, online, on a mobile app) and receive consistent service and support. AI can enhance omnichannel customer interaction by providing a unified view of the customer across channels, enabling personalized interactions, and ensuring continuity of service (Chen et al., 2017).

AI technologies such as chatbots and virtual assistants have become increasingly prevalent in customer service. These tools use Natural Language Processing and Machine Learning to understand and respond to customer queries in natural language, offering information, handling simple transactions, or escalating complex issues to human agents. This can improve the efficiency and availability of customer service, reduce response times, and free up human agents to handle more complex or sensitive issues (Xu et al., 2021).

Social media has emerged as a vital channel for customer interaction. Businesses use social media to engage with customers, share information, gather feedback, and manage customer relationships. AI can enhance social media interaction by analyzing large volumes of social media data to identify trends, sentiment, and influencers, automating responses to common queries, and personalizing social media content or ads (He et al., 2017).

With the rise of smart speakers and voice assistants, voice has become a significant channel for customer interaction. AI technologies such as speech recognition and synthesis enable businesses to interact with customers via voice, offering a hands-free, natural, and often highly convenient user experience (Hoy, 2018).

While AI can greatly enhance customer interaction, it also introduces several challenges and ethical considerations. These include issues related to data privacy and security, potential biases in AI algorithms, and the need to balance automation with human touch. Businesses must address these challenges to ensure they deliver ethical, responsible, and effective customer interaction (Huang and Rust, 2021).

Predictive personalization refers to the use of data analysis and predictive modeling to tailor experiences, communications, or products to an individual's predicted needs or preferences. This advanced form of personalization is driven by AI technologies, such as Machine Learning (ML) and Predictive Analytics, which can analyze large volumes of data, identify patterns, and make accurate predictions about future behavior (Huang and Rust, 2021).

The foundation of predictive personalization is data. This includes both historical data (e.g., past transactions, interactions, or behaviors) and real-time data (e.g., current browsing behavior or location). Businesses collect and analyze this data to build a comprehensive understanding of each customer's behavior, preferences, and needs (Chen et al., 2012).

Once a sufficient amount of data has been collected, it can be used to train a predictive model. This is a Machine Learning algorithm that can identify patterns in the data and make predictions about future behavior or outcomes. For example, a predictive model might predict which products a customer is likely to be interested in, when they are likely to make a purchase, or how they are likely to respond to a particular marketing message (Provost and Fawcett, 2013).

Based on the predictions made by the model, businesses can then tailor their interactions, communications, or products to each individual customer. This can involve personalizing the content, format, or timing of communications, recommending specific products or services, or adapting the user experience to meet the customer's predicted needs or preferences. The goal is to offer a personalized experience that not only meets but anticipates the customer's needs, thereby enhancing engagement and satisfaction (Huang and Rust, 2021).

Predictive personalization is not a one-time process, but a continuous cycle of learning and adaptation. As more data is collected, the predictive model can be updated and refined, leading to more accurate predictions and more effective personalization. Businesses also need to continuously monitor and evaluate the effectiveness of their personalization efforts, and adjust their strategies as needed (Provost and Fawcett, 2013).

While predictive personalization offers significant potential benefits, it also presents several challenges. These include the need for large amounts of high-quality data, the complexity of predictive modeling, potential issues with user privacy and data security, and the risk of over-personalization, where customers may feel their privacy is being invaded. Businesses need to manage these challenges effectively to realize the full benefits of predictive personalization (Huang and Rust, 2021).

AI applications also extend to predictive analytics, allowing businesses to forecast future trends and adjust their strategies accordingly. Predictive analytics can be particularly useful in demand forecasting, inventory management, and marketing strategies. By leveraging AI-powered predictive analytics, businesses can optimize their operations and mitigate potential risks (Davenport & Ronanki, 2018).

AI can help businesses in risk management and regulatory compliance by detecting irregular patterns and potential fraud. This is particularly relevant in sectors like finance where regulatory compliance is crucial, and the volume of transactions makes manual monitoring impractical (Arrieta et al., 2020).

In the modern business landscape, risk management and compliance are critical elements for the survival and success of organizations. Through the adoption of AI technologies, businesses can enhance their risk management strategies and meet compliance requirements more effectively. AI can analyze vast amounts of data at a pace beyond human capabilities, detect patterns, anomalies, and potential risks that could be missed by traditional systems (Bholat et al., 2019).

AI, particularly machine learning and predictive analytics, can identify and assess potential risks that a company might face. This could be in financial sectors for credit scoring or fraud detection, in cyber security for identifying potential threats, or in operations for predicting potential bottlenecks or failures. AI algorithms can analyze historical data to understand patterns and predict future risk scenarios (Arner et al., 2016).

Risk detection and prediction is a crucial aspect of risk management in any organization. With the advent of artificial intelligence (AI), these processes have become significantly more advanced and efficient, particularly through the use of machine learning (ML) and predictive analytics.

Machine learning, a subset of AI, is a method of data analysis that automates the building of analytical models. It uses algorithms that iteratively learn from data, allowing computers to find hidden insights without being explicitly programmed where to look. ML can be used in risk detection by analyzing patterns in vast quantities of data to identify potential risks. For example, in the financial sector, ML algorithms can analyze transactional data to identify suspicious patterns that may indicate fraud (Bholat et al., 2019).

Predictive analytics is a form of advanced analytics that uses both new and historical data to forecast activity, behavior, and trends. It involves applying statistical analysis techniques, analytical queries, and automated machine learning algorithms to data sets to create predictive models that place a numerical value — or score — on the likelihood of a particular event happening. Predictive analytics can be used to anticipate potential future risks based on historical data. For instance, predictive analytics can help forecast potential operational failures in manufacturing or identify customers likely to default on their loans (Wang and Alexander, 2014).

One of the most impactful applications of AI in risk detection and prediction is its ability to perform these functions in real-time. Traditional methods of risk management often involve time lags, but AI can identify and assess risks as they occur. For instance, AI systems can analyze social media feeds, news reports, and market trends to identify real-time risks that could impact a business (Russom, 2011).

While the application of AI in risk detection and prediction offers considerable benefits, it also presents challenges. These include data privacy concerns, the quality and relevance of the data used, and the interpretability of AI models. Furthermore, while AI can greatly assist in risk detection and prediction, human oversight remains essential to understand and act on these risks appropriately (Mittelstadt et al., 2016).

Regulatory compliance is another area where AI can provide significant benefits. Regulations vary across industries and regions and keeping up with this complexity can be challenging. AI-powered tools can scan and understand numerous regulatory texts, updates, and precedents, helping businesses stay compliant. In addition, AI can automate reporting and ensure consistent compliance practices across the organization (Arner et al., 2016).

Cybersecurity is a broad and critical field aimed at protecting systems, networks, and data from cyber threats. These threats can range from theft, damage, or unauthorized access to sensitive information. With the rapid growth and reliance on digital platforms, the importance of robust cybersecurity measures has become increasingly crucial. The application of Artificial Intelligence (AI) in cybersecurity offers new and dynamic ways of ensuring data and system protection (Buczak & Guven, 2016).

AI technologies, including machine learning (ML) and natural language processing (NLP), are being widely used in cybersecurity. AI's ability to analyze and learn from large volumes of data can help detect and predict security threats in real-time, enhancing response and remediation efforts. For instance, ML can identify patterns and anomalies in network traffic, enabling early detection of potential threats (Ahmed et al., 2016).

AI enhances the ability to detect and predict threats by learning from past security incidents and analyzing current data patterns. Through machine learning algorithms, AI can quickly sift through vast amounts of data, identify abnormal behavior, and alert security teams. Additionally, AI can forecast future threats based on the identified patterns, enabling proactive security measures (Sharma & Chen, 2020).

AI significantly improves the incident response time by automating the detection and mitigation of threats. AI systems can autonomously isolate affected systems, block suspicious IP addresses, and apply necessary security patches, thus limiting the spread and impact of cyber threats (Buczak & Guven, 2016).

AI plays a vital role in UEBA, which involves monitoring and analyzing the behavior of users and entities in a network to detect any anomalies. AI can learn normal behavioral patterns and swiftly flag any deviations, indicating potential malicious activities. UEBA has been instrumental in detecting insider threats and compromised accounts (Sharma & Chen, 2020).

Despite AI's numerous advantages in cybersecurity, it also presents certain challenges. One of the main issues is the potential misuse of AI by malicious actors to create sophisticated cyber-attacks. Additionally, the accuracy of AI in detecting threats heavily depends on the quality of the training data. Biased or incomplete data can lead to false positives or overlooked threats. Lastly, the 'black box' nature of some AI models may create difficulties in interpreting why a particular behavior was flagged as a threat (Veale & Binns, 2017).

Fraud poses significant risk to businesses, particularly in financial and online retail sectors. AI can analyze transaction patterns in real-time and flag suspicious activities, such as unusually large transactions, frequent transactions in a short time, or transactions from unusual locations. Machine learning algorithms learn from past instances of fraud to detect future fraudulent activities (Bholat et al., 2019).

With increasing digitalization, cybersecurity risks have amplified significantly. AI can proactively detect potential vulnerabilities, predict cyber threats and help in automating responses to such threats. Machine learning algorithms can identify abnormal network behaviors and alert for potential intrusions (Buczak and Guven, 2016).

While AI applications in risk management and compliance provide numerous advantages, they also bring about challenges, mainly relating to data privacy and ethical considerations. Misuse of AI could lead to invasion of privacy and discrimination. Ensuring AI systems are transparent, explainable, and ethical is therefore crucial (Mittelstadt et al., 2016).

Artificial Intelligence (AI) has rapidly evolved as a critical tool in driving sustainable energy practices and enabling the transformation towards Industry 4.0. This section explores the diverse applications of AI in the renewable energy sector, manufacturing, and industrial processes and highlights potential challenges and future prospects.

AI can enhance the efficiency and optimization of renewable energy systems, contributing to a more sustainable energy sector. Machine learning algorithms can predict energy production and demand, facilitating better energy management and grid stability. For instance, AI can predict wind speed and solar irradiance, allowing for more accurate forecasting of energy output from wind and solar power plants (Schapire, 2019). AI also supports the integration of electric vehicles and energy storage systems into the power grid, paving the way for smart grids.

AI is integral to improving energy efficiency in buildings and industrial processes. It can manage and control HVAC systems, lighting, and other power-consuming devices based on occupancy patterns and external environmental conditions (Auffhammer, 2018). By identifying energy consumption patterns and inefficient appliances, AI can recommend measures to reduce energy use and lower emissions.

Industry 4.0 refers to the fourth industrial revolution characterized by smart manufacturing and industrial operations, cyber-physical systems, Internet of Things (IoT), and cloud computing. AI plays a pivotal role in this transformation. AI algorithms can optimize production processes, enhance quality control, and predict maintenance needs, thereby reducing downtime (Schwab, 2017). AI also enables a high degree of automation and customization in manufacturing, contributing to increased productivity and cost savings.

Artificial Intelligence (AI) is a key driver of Industry 4.0, often referred to as the fourth industrial revolution. This revolution, characterized by digitalization and interconnectivity, aims to create 'smart factories' that bring about a step-change in the efficiency and flexibility of production processes (Schwab, 2017).

AI has a significant impact on the manufacturing process, revolutionizing how products are designed, produced, and delivered. Machine learning algorithms, for instance, can analyse complex datasets and optimize production processes, improving quality control, and reducing waste. Predictive maintenance, powered by AI, can anticipate equipment failure and schedule maintenance, thereby reducing downtime and extending the lifespan of machinery (Lee et al., 2014).

AI-driven automation is another transformative feature of Industry 4.0. It facilitates the automation of complex tasks, resulting in increased productivity and cost efficiency. For instance, autonomous robots equipped with AI capabilities can perform tasks with minimal human intervention, working alongside humans in a collaborative and safe manner. These robots can adapt to changing environments and learn new tasks, bringing a new level of flexibility to manufacturing operations (Rosenberg et al., 2019).

AI is also revolutionizing supply chain management. AI algorithms can analyse vast amounts of data to forecast demand, optimize inventory, and improve logistics. This results in lower costs, reduced waste, and higher customer satisfaction. Furthermore, AI can improve the visibility and transparency of supply chains, enabling companies to manage risks and make more informed decisions (Ivanov et al., 2019).

AI plays a critical role in cyber-physical systems (CPS), which are integrations of computation, networking, and physical processes. AI algorithms can process data from sensors, interpret it, and make decisions or predictions. This capability enables real-time monitoring and control of industrial processes, enhancing efficiency, safety, and reliability (Monostori, 2014).

AI is not only facilitating the transition to Industry 4.0 but also redefining the very nature of manufacturing and industrial processes. However, the successful implementation of AI requires addressing several challenges, including data privacy and security, ethical issues, and the need for skills training (Liao et al., 2017). Despite these challenges, the future of AI in Industry 4.0 is promising, with further advancements likely to yield even greater efficiencies and innovations.

Artificial intelligence (AI) and automation have grown increasingly interconnected as technology has advanced, with AI algorithms driving much of the development in modern automation. This merging of technologies is profoundly changing many sectors of the economy, from manufacturing to services, and has the potential to greatly increase productivity while also raising important questions about the future of work.

AI-driven automation in manufacturing is making significant strides in improving the efficiency and reliability of production processes (Lee et al., 2014). This kind of automation can handle a variety of tasks, from mundane, repetitive jobs to more complex operations. It's transforming traditional manufacturing and assembly tasks, but it's also playing a crucial role in areas like quality control, predictive maintenance, and safety regulation. For example, AI-powered robots and machinery can detect inconsistencies or defects in products more quickly and accurately than human operators (Rosenberg et al., 2019).

Intelligent process automation (IPA) is the combination of artificial intelligence and automation. In contrast to traditional automation, which is often rule-based, IPA can learn and improve over time. This is made possible by machine learning algorithms that allow the system to learn from its mistakes and improve its performance based on feedback. This ability to learn and adapt makes IPA particularly useful in fields where processes are complex or variable, such as customer service or data analysis.

Cognitive automation is a further extension of AI and automation, combining artificial intelligence, machine learning, and cognitive technologies to automate knowledge-intensive processes. It goes beyond automating manual tasks and starts to automate cognitive tasks that traditionally require human intelligence. This includes tasks such as decision-making, problem-solving, and learning. Cognitive automation could transform a wide range of sectors, including healthcare, law, and finance, by automating complex tasks that require human-like understanding and reasoning.

The increasing integration of AI and automation is likely to have a significant impact on the labour market. On the one hand, these technologies could increase productivity, lead to new job opportunities, and improve the quality of work by taking over mundane tasks. On the other hand, they could also displace certain jobs, particularly routine, manual jobs, leading to job losses in certain sectors. Therefore, managing this transition and ensuring that workers are re-skilled and up-skilled for the jobs of the future will be a key challenge (Arntz et al., 2016).

The continued integration of AI and automation promises to bring significant advancements in productivity and efficiency. But it will also present challenges that need to be managed to ensure a just transition to an increasingly automated economy.

Cognitive Automation represents the third wave of automation, extending the capabilities of rule-based robotic process automation (RPA) and intelligent automation (IA) systems to incorporate more complex tasks traditionally associated with human cognition, such as understanding, reasoning, and learning.

At the heart of cognitive automation lies Natural Language Processing (NLP), a branch of AI that gives machines the ability to read, understand, and derive meaning from human languages (Hovy, 2018). This includes understanding sentiment, context, and semantic nuances within textual data. Through NLP, cognitive automation systems can interact with humans more naturally and make sense of unstructured data.

Cognitive automation systems can be programmed to reason and make decisions based on a given set of inputs. By leveraging technologies like machine learning and artificial intelligence, these systems can analyze a vast amount of data, identify patterns, and make informed decisions much more quickly and accurately than a human could (Russell & Norvig, 2016).

Cognitive automation systems have the ability to learn and adapt over time. Using machine learning algorithms, these systems can learn from their previous actions and improve their performance. This includes refining their decision-making processes, improving their ability to recognize patterns, and adapting to new situations (Mitchell, 2017).

Cognitive automation is applicable in a wide range of industries. In healthcare, it's used to analyze patient data and suggest treatment plans. In finance, it's employed to detect fraudulent transactions. In customer service, cognitive automation can be used to handle customer inquiries and complaints. Moreover, it's increasingly used in data analysis, where it can sift through vast amounts of data and extract meaningful insights.

While cognitive automation presents significant opportunities, it also brings a set of challenges and ethical considerations. There are concerns about job displacement, as these systems can potentially replace humans in certain tasks. Issues related to data privacy and security are also paramount, as these systems often rely on large amounts of data. Furthermore, ensuring that these systems make ethical and unbiased decisions is a complex yet crucial challenge (Dignum, 2017). Thus, cognitive automation represents a significant step forward in automation technology, enabling the automation of complex tasks that require human-like understanding and reasoning. However, its implementation requires careful consideration of several challenges and ethical issues.

Despite the numerous benefits of AI in sustainable energy and Industry 4.0, several challenges need to be addressed. These include data security and privacy concerns, the need for significant investments in infrastructure, and a lack of skilled personnel to implement and manage AI systems. Furthermore, ethical considerations associated with job displacement due to automation require attention (Ransbotham et al., 2019).

Looking ahead, the integration of AI with other emerging technologies like blockchain could offer new possibilities for peer-to-peer energy trading and secure data management. The convergence of AI and quantum computing may also usher in a new era of computational capabilities, driving further advancements in these sectors.

Artificial Intelligence (AI) has significantly influenced various aspects of business, and Customer Relationship Management (CRM) is not an exception. CRM systems powered by AI algorithms have greatly enhanced businesses' ability to interact, understand, and serve their customers, thereby improving customer satisfaction, loyalty, and ultimately, profitability (Ngai et al., 2018).

AI plays a pivotal role in predicting customer behaviour, thus allowing businesses to personalize their interactions with each customer. AI algorithms can analyze past customer behaviour, transactions, and interactions, and use this information to predict future actions, such as which products a customer might be interested in or when they might churn. These insights can be used to tailor the marketing strategies to individual customer needs (Sharma et al., 2019).

Predictive customer analytics is an application of AI in customer relationship management that aims to forecast future customer behavior based on historical data. It allows businesses to make proactive and data-driven decisions that can enhance customer satisfaction, engagement, and loyalty (Xu & Frankwick, 2016).

By analyzing past transactions and interactions, AI algorithms can identify patterns and trends in customer behavior. For instance, they can determine what products or services a customer prefers, how frequently they make purchases, and what factors drive their purchasing decisions. This information can help businesses understand their customers on a deeper level, which in turn, can guide marketing and sales strategies (Ngai et al., 2018).

With predictive analytics, businesses can deliver a personalized experience to their customers. They can predict what products or services a customer might be interested in based on their past behavior and preferences. Then, they can tailor their marketing messages, product recommendations, and promotional offers to match these individual preferences. Personalization can lead to higher customer engagement, better conversion rates, and improved customer loyalty (Li et al., 2019).

Predictive analytics can also be used to identify customers who are likely to churn, i.e., stop doing business with the company. By identifying the signs of customer dissatisfaction early, businesses can take proactive steps to retain these customers, such as reaching out to them with special offers or addressing their concerns (Lemmens & Gupta, 2017).

Predictive customer analytics can help businesses anticipate future sales trends. By analyzing patterns in historical sales data, AI algorithms can forecast future sales for specific periods, products, or regions. Accurate sales forecasting can guide strategic decisions related to inventory management, budgeting, and goal setting (Rao & Kumar, 2020).

Despite its potential benefits, predictive customer analytics comes with challenges. These include the need for high-quality and representative data, the complexity of building accurate predictive models, and the necessity of balancing personalization with customer privacy (Sharma et al., 2019). Predictive customer analytics leverages AI to turn historical customer data into valuable insights and predictions. This enables businesses to understand their customers better, personalize their interactions, retain valuable customers, and accurately forecast sales.

AI-driven chatbots and virtual assistants have become an essential part of CRM systems. These digital agents can simulate human conversation and are capable of handling a broad array of customer interactions, including answering queries, setting appointments, or guiding users through complex processes. They offer businesses the ability to provide 24/7 customer service, improve response times, and enhance overall customer experience (Feine et al., 2019).

Chatbots and virtual assistants are AI-enabled tools that allow businesses to automate their customer interactions. They leverage natural language processing and machine learning algorithms to understand and respond to customer queries in a human-like manner (Kerly, Hall & Bull, 2007).

Chatbots are AI-powered software designed to simulate human-like conversations with users through messaging platforms, websites, or mobile apps. They can answer customer queries, provide product recommendations, assist with bookings or purchases, and even provide personalized content based on user preferences. These interactions happen through text-based messaging, although some advanced chatbots also support voice communication (Brandtzaeg & Følstad, 2017).

Virtual assistants (VAs) take the capabilities of chatbots a step further. While chatbots are typically used for simple, single-turn tasks, VAs are designed to manage more complex, multi-turn conversations. They can understand the context of a conversation, remember past interactions, and carry out a broader range of tasks. Examples of VAs include Amazon's Alexa, Google Assistant, and Apple's Siri. They can set reminders, make phone calls, send texts, play music, control smart home devices, and provide information from the web, among other tasks (Luger & Sellen, 2016).

Both chatbots and VAs are becoming increasingly prevalent in businesses due to their potential to improve customer service, increase engagement, and reduce operational costs. They can provide 24/7 customer support, handle multiple customers simultaneously, and instantly answer common queries, freeing up human agents to handle more complex issues.

Moreover, they can be used in different areas of a business, such as sales, marketing, HR, and IT support (Shum, He, & Li, 2018).

Chatbots and VAs can deliver personalized experiences to customers. Based on the data collected from past interactions, they can provide customized recommendations, tailor their responses, and even predict future customer needs. This can enhance customer satisfaction and loyalty (Hoy, 2018).

Sentiment analysis, also known as opinion mining, is a field of study that analyses people's opinions, sentiments, evaluations, attitudes, and emotions from written language. It is one of the most active research areas in natural language processing and also widely studied in data mining, Web mining, and text mining (Liu, 2012).

Sentiment analysis can be categorized into three main types: a) Fine-grained Sentiment Analysis: This goes beyond just positive, neutral, or negative and might divide sentiment into categories such as "very positive", "positive", "neutral", "negative", "very negative". b) Aspect-based Sentiment Analysis: This not only identifies the sentiment but also the entity in question. For instance, "The battery life of this phone is great" - the sentiment 'great' is associated with the aspect 'battery life'. C) Emotion detection: This goes beyond positive or negative and identifies specific emotions such as happiness, frustration, anger, sadness, and so on.

There are typically two methods of sentiment analysis: a) Machine Learning approach: This method treats sentiment analysis as a classification problem where a classifier is fed a large amount of pre-labeled examples of positive, negative, and neutral sentiments. The classifier is then trained on these examples and then used to classify new examples.

Different types of machine learning models can be used, including but not limited to Naive Bayes, Linear Regression, Support Vector Machines, and deep learning models (Pang, Lee & Vaithyanathan, 2002). b) Lexicon-based approach: This method uses a sentiment lexicon, a list of lexical features that are typically labeled according to their semantic orientation as either positive or negative. Sentiment scores are assigned to the phrases in the text, and the scores are then aggregated to determine the overall sentiment of the text (Taboada et al., 2011).

Sentiment analysis is widely used across industries for various applications: a) In business, companies use sentiment analysis to understand customer opinions about their brand and products, to monitor and manage their reputation, and to understand customer needs. b) In politics, sentiment analysis is used to track public opinion of candidates or policy issues and to detect fluctuations in sentiment over time. c) With the explosion of user-generated content on social media, sentiment analysis is being used to monitor sentiments on these platforms and respond more effectively to customer complaints or praise.

While sentiment analysis has advanced significantly, there are still many challenges. For instance, understanding the context to determine the sentiment of a word or phrase can be tricky. Sarcasm is another major challenge as it often requires understanding subtle nuances in the text.

Despite their benefits, the deployment of chatbots and VAs also comes with challenges. Ensuring accurate understanding and response generation in different contexts, maintaining user privacy and security, and managing the potential negative impacts on employment are some of the key issues that need to be addressed (Bickmore, Caruso, & Clough-Gorr, 2005). In conclusion, chatbots and virtual assistants have become an integral part of AI-driven customer relationship management, offering businesses the opportunity to automate and personalize their customer interactions.

AI in CRM can also be utilized for sentiment analysis, where customer opinions, reviews, and communications are analyzed to identify their sentiments toward a product, service, or brand. This technology uses Natural Language Processing (NLP) and machine learning techniques to classify text into positive, neutral, or negative sentiments. Such insights can help businesses improve their products and services based on customer feedback (Cambria & White, 2014).

Routine CRM tasks such as data entry, meeting scheduling, follow-ups, and reporting can be efficiently automated with the help of AI. Automation not only reduces the manual effort involved in these tasks but also reduces the chances of errors, enabling the sales team to focus more on strategic tasks (Schmid, 2020).

Customer Relationship Management (CRM) automation is the process of automating repetitive, manual tasks in the CRM process. This automation can greatly enhance customer engagement, streamline sales and customer service workflows, and increase productivity (Schwartz & Piening, 2019). With CRM automation, companies can spend more time on critical tasks and decision-making rather than mundane data entry or administrative tasks. a) Sales Automation: This involves automating the sales cycle, from initial customer contact to closing a deal. It can include tracking and managing leads, automating follow-up emails, setting reminders for follow-up calls, and creating automatic quotes or proposals. b) Marketing Automation: CRM automation can streamline various marketing tasks, such as segmenting customers based on their behavior, preferences or demographics, sending personalized emails or messages at optimal times, and tracking the effectiveness of marketing campaigns. c) Service Automation: This can involve automating various customer service tasks, such as routing customer queries to the right department or person, generating automatic responses to common queries, and setting reminders for follow-ups. d) Analytics and Reporting Automation: CRM automation tools can generate reports and analytics that offer insights into sales performance, customer behavior, and campaign effectiveness. They can also create dashboards that visualize this data in real-time.

Automation reduces the time and effort required for routine, manual tasks, allowing sales and customer service teams to focus more on engaging with customers. Automated systems minimize human error in data entry and reporting, ensuring that the data in the CRM system is accurate and reliable. Automation can help businesses provide faster, more responsive service to customers, enhancing customer satisfaction and loyalty. Automated analytics and reporting provide insights that can guide strategic decision-making.

While there are significant benefits to CRM automation, it's not without its challenges. These can include integrating the automation tools with existing systems, ensuring data privacy and security, training staff to use the tools effectively, and maintaining the human touch in customer interactions.

AI algorithms can analyze historical sales data and identify patterns that contribute to sales conversions. This helps in predicting future sales trends and allows businesses to make informed decisions about inventory management, budgeting, and goal setting. AI-driven sales forecasting provides more accurate and reliable predictions compared to traditional methods (Rao & Kumar, 2020).

Artificial Intelligence (AI) has increasingly been applied in the field of sales forecasting, providing a more accurate, efficient, and dynamic approach to predict sales trends. AI-based sales forecasting uses machine learning algorithms to analyze historical sales data and identify patterns, which it then uses to predict future sales (Bischl et al., 2022).

Traditional sales forecasting often relies on statistical methods and intuition. While these approaches can be effective, they have limitations. For instance, they might not account for non-linear relationships or complex interactions among variables.

In contrast, AI-based forecasting employs machine learning algorithms that can handle complex, high-dimensional data, identify hidden patterns, and learn from these patterns to make accurate predictions. These algorithms can handle a wide variety of factors - such as seasonality, promotions, pricing changes, market trends, and even external factors like weather or economic indicators - that can influence sales (Benidis et al., 2020).

AI-based sales forecasting systems typically involve the following steps: a) Data collection and pre-processing: This involves gathering historical sales data and other relevant information, and then cleaning and structuring the data for analysis. b) Feature selection and extraction: This involves identifying the most relevant variables or features that influence sales. c) Model training: This involves using machine learning algorithms to learn from the historical data. The algorithms adjust their parameters based on the patterns they identify in the data. d) Validation and testing: This involves testing the model's predictions against actual data to assess its accuracy. e) Forecasting: Once the model is trained and validated, it can be used to forecast future sales based on current and predicted conditions.

The key benefits of AI-based sales forecasting include: a) Accuracy: AI algorithms can identify complex patterns and consider numerous factors, leading to more accurate sales forecasts (Benidis et al., 2020). b) Efficiency: AI can process vast amounts of data much faster than humans, significantly speeding up the forecasting process. c) Adaptability: AI models can continuously learn from new data, allowing them to adapt to changes in market conditions or consumer behavior. d) Data-driven decision making: By providing more accurate forecasts, AI helps businesses make better-informed decisions about inventory management, production planning, budgeting, and other aspects of business strategy.

Despite its many benefits, integrating AI into CRM systems presents challenges. These include issues related to data privacy and security, the need for quality and representative data for training AI models, the complexity of integrating AI with existing CRM systems, and the requirement for continuous monitoring and adjustment of AI models to ensure their performance and fairness (Gupta et al., 2020).

In summary, the application of AI in CRM systems offers numerous opportunities to enhance customer experience and operational efficiency. However, businesses must address the challenges associated with AI integration to fully harness its potential benefits. Automation in CRM can transform how companies engage with their customers. By automating repetitive tasks, businesses can provide better service, enhance customer relationships, and gain a competitive edge (Schwartz & Piening, 2019).

Artificial Intelligence (AI) is making a significant impact in the B2B sector, offering innovative solutions that improve efficiency, decision-making, customer service, and overall business strategies. By leveraging AI, B2B companies can gain competitive advantages, create personalized experiences for clients, and optimize their operations.

In the B2B space, personalized marketing and sales are paramount. Unlike B2C, where marketers target a broader audience, B2B marketers deal with a smaller, more specific group. AI can help here by analyzing vast amounts of data to identify patterns and trends that can be used to deliver personalized content to potential clients (Li et al., 2020). Personalization in the Business-to-Business (B2B) environment involves tailoring sales and marketing efforts to the unique needs and characteristics of each business client. This process is important because it allows B2B companies to build deeper relationships with clients, leading to increased customer loyalty and sales. Artificial Intelligence (AI) plays a pivotal role in facilitating personalized marketing and sales in B2B scenarios, as it can analyze large amounts of data to derive insightful trends and patterns.

Personalization starts with understanding the client's needs, preferences, and behavior. AI algorithms can analyze various types of data, such as transaction history, website behavior, and social media interactions, to gain insights into a client's preferences and needs. This understanding can then be used to tailor marketing and sales efforts to each client (Li et al., 2020). For example, if a client regularly purchases a particular product or service, a company can customize its marketing messages to highlight related products or services that may be of interest.

AI-powered content management systems can generate personalized content for each client. This could involve creating customized emails, newsletters, or blog posts that cater to the client's specific interests or needs. Similarly, sales pitches can be personalized based on the client's purchasing history and preferences.

Predictive analytics uses AI to predict future outcomes based on historical data. In the context of B2B personalized marketing and sales, predictive analytics can be used to forecast a client's future needs or purchasing behavior (Chen et al., 2019). This information can be used to proactively address these needs and enhance the client's experience.

Account-based marketing (ABM) is a strategic approach to B2B marketing in which companies focus on individual client accounts as markets of their own. AI can help identify key accounts based on data analysis and then deliver personalized marketing strategies to these accounts (Li et al., 2020).

AI can also automate many aspects of the sales process, from lead generation to closing a sale. AI-powered Customer Relationship Management (CRM) systems can automate tasks like data entry, email marketing, and follow-ups. Moreover, they can predict sales outcomes, helping sales teams focus their efforts on the most promising leads (Huang and Rust, 2018). In conclusion, AI has revolutionized the way B2B companies approach personalized marketing and sales, allowing them to deliver more targeted, effective, and responsive service.

Machine learning algorithms can predict customer preferences and suggest the most effective strategies to engage with them. AI can also automate email marketing campaigns, segment customers, and provide insights into customer behavior. Furthermore, AI-powered CRM systems can forecast sales, aiding in decision-making and business strategy.

AI is a game-changer in supply chain management and logistics. Companies use AI to forecast demand, manage inventory, optimize routes, and even automate warehouses (He et al., 2020). Machine learning models can predict potential disruptions in the supply chain and recommend contingency plans. Additionally, AI-powered robotics are being used in warehouses for tasks like sorting and packing goods, increasing operational efficiency.

B2B businesses are implementing AI to automate various tasks, from data entry and report generation to more complex tasks like drafting contracts. Intelligent automation combines AI and Robotic Process Automation (RPA) to automate and optimize business processes. This not only improves efficiency but also reduces the risk of human errors and allows employees to focus on more strategic tasks (Lacity et al., 2022).

Intelligent Automation (IA) represents the intersection of artificial intelligence (AI) and automation, creating systems that can automate both routine tasks and more complex processes by learning and adapting over time (Davenport and Ronanki, 2018).

Intelligent automation comes in different forms, including robotic process automation (RPA), which automates routine tasks, cognitive automation, which handles complex tasks requiring problem-solving or decision-making abilities, and machine learning, which enables systems to learn and improve from experience without being explicitly programmed (Wang, Ramadani, & Phan, 2020).

Intelligent automation has wide-ranging applications across industries, from improving operational efficiency in manufacturing and supply chain management, to enhancing customer interactions in the retail and service sectors. In healthcare, for example, IA can automate patient scheduling, claims management, and data analysis, allowing professionals to focus on patient care (Panetta, 2019).

By combining the capabilities of AI and automation, intelligent automation can significantly increase efficiency, reduce costs, improve accuracy, and enable businesses to make data-driven decisions. It also helps organizations to scale their operations, enabling them to handle larger volumes of tasks and data without a corresponding increase in human resources (Davenport and Ronanki, 2018).

Despite its many advantages, intelligent automation also comes with potential challenges and risks. These include technical complexities related to integration with existing systems, data privacy and security issues, regulatory and compliance considerations, and the potential impact on jobs and the workforce (Wang, Ramadani, & Phan, 2020).

As AI continues to evolve, intelligent automation is expected to become increasingly sophisticated and prevalent. It will likely play a key role in Industry 4.0, driving the digital transformation of industries and leading to what some experts call the "autonomous enterprise" (Panetta, 2019).

In summary, intelligent automation is a transformative technology that is reshaping business operations across sectors. It offers significant benefits in terms of efficiency, cost savings, and decision-making capabilities, but also poses challenges that need to be carefully managed.

AI algorithms can sift through vast amounts of data to extract actionable insights, which are invaluable in decision-making. Predictive analytics can forecast trends and prescriptive analytics can suggest actions to take. AI can also provide real-time analytics, giving B2B businesses the ability to respond to changes in the market promptly (Sivarajah et al., 2021).

AI-powered chatbots and virtual assistants are increasingly used in B2B businesses to provide 24/7 customer support. These AI systems can handle a variety of tasks like answering queries, setting appointments, and providing product information, delivering a better customer experience (Luo et al., 2019). In conclusion, AI offers significant opportunities to innovate and optimize in the B2B sector. However, adopting AI also comes with challenges, such as the need for high-quality data, privacy and security issues, and the need for digital transformation.

Business-to-Business (B2B) decision-making and analytics involve the use of data analysis tools, techniques, and artificial intelligence to inform strategic and operational decisions in B2B environments. These decisions could relate to marketing, sales, supply chain management, risk management, and more (Ransbotham, Kiron, Prentice, & Heine, 2017).

B2B analytics can take various forms, including predictive analytics, which uses historical data to predict future trends; prescriptive analytics, which suggests optimal actions based on the analysis of complex data sets; and descriptive analytics, which provides insights into past business performance (Ransbotham et al., 2017).

In a B2B context, analytics play a critical role in decision-making processes. For example, predictive analytics can help businesses anticipate customer needs and tailor their offerings accordingly, improving customer satisfaction and loyalty (Verhoef, Kooge, & Walk, 2016). Moreover, prescriptive analytics can aid in supply chain management, by offering insights on optimal inventory levels or delivery routes (Shapiro, 2017).

Artificial intelligence has a significant role to play in B2B analytics, given its ability to process large volumes of data and extract meaningful insights. Machine learning algorithms, for instance, can be used to analyze customer data and identify patterns that human analysts might overlook. This can lead to more accurate sales forecasting, improved customer segmentation, and more effective marketing strategies (Chui, Manyika, & Miremadi, 2016).

Despite its potential benefits, B2B analytics also presents some challenges. These include data privacy concerns, the need for high-quality and relevant data, and the risk of bias in AI algorithms. Moreover, there may be resistance from employees who fear that AI and analytics could render their roles redundant (Ransbotham et al., 2017).

As the technology continues to evolve, the use of analytics in B2B decision-making is expected to become more widespread and sophisticated. Emerging trends include the integration of AI with Internet of Things (IoT) data for real-time analytics, and the use of natural language processing for advanced sentiment analysis in B2B marketing (Chui, Manyika, & Miremadi, 2016).

In summary, B2B decision-making and analytics, enabled by artificial intelligence, provide businesses with valuable insights that can inform strategic and operational decisions, thereby enhancing business performance and competitiveness.

In the Business-to-Business (B2B) landscape, customer support and service are critical components that influence client satisfaction, loyalty, and ultimately, commercial success. In contrast to Business-to-Consumer (B2C) models, B2B transactions often involve higher stakes, complex multi-stakeholder scenarios, long sales cycles, and a high level of customization, all of which demand robust customer support and service frameworks (Tuli, Kohli & Bharadwaj, 2007).

B2B customer support is typically multi-layered and personalized due to the complexity of the products and services involved. It often includes technical support, product training, maintenance services, and ongoing consultation. This support helps businesses maximize their investment, navigate product complexities, and solve problems effectively and efficiently (Roos, 2012).

Artificial Intelligence (AI) is playing an increasingly important role in enhancing B2B customer support. AI-powered chatbots and virtual assistants, for example, can provide instant support to B2B customers, answering queries round the clock and escalating complex issues to human agents. This not only enhances the customer experience but also makes the support process more efficient (Featherman & Hajli, 2016).

Moreover, predictive analytics can help businesses anticipate customer issues and proactively provide solutions, thereby improving customer satisfaction and reducing support costs (Nguyen, Newby & Macaulay, 2015).

In the B2B context, customer service often involves Service Level Agreements (SLAs), which are contractual commitments to provide a certain level of service. SLAs set clear expectations about service quality, timelines, and redress mechanisms, ensuring that both parties have a common understanding of the terms of service (Tuli et al., 2007).

The nature of B2B customer support and service is evolving with advancements in technology. Today's digital tools offer B2B firms the ability to track customer interactions, analyze customer data, and gain insights into customer needs and behaviors. This allows for more personalized and proactive customer service, fostering stronger customer relationships (Roos, 2012).

The future of B2B customer support lies in further personalization, increased use of AI and machine learning, and more proactive service. These advancements will likely make B2B customer support more predictive, personalized, and efficient, enabling businesses to deliver superior customer experiences and build long-term customer relationships (Featherman & Hajli, 2016).

The widespread integration of AI in various sectors, including business processes, has sparked significant ethical and safety debates. This is because AI applications, while enabling efficiency and productivity, also present numerous challenges relating to privacy, bias, accountability, transparency, and security. Understanding these implications is key to developing responsible AI practices (Crawford & Calo, 2016).

Privacy is one of the most significant concerns associated with AI. Machine learning algorithms often rely on large amounts of data to make accurate predictions and decisions, which may include sensitive personal or corporate information. Without appropriate safeguards and consent protocols, this can lead to privacy breaches, data misuse or data leakage (Sweeney, 2013).

The notion of privacy in the context of artificial intelligence refers to the safeguarding of sensitive and personal data which is often used to train and operate AI systems. As AI systems continue to become increasingly integral in various domains, it becomes paramount to ensure that the privacy of individuals is protected. Privacy in AI can be viewed from three main perspectives: data collection, data usage, and data storage (Richards & King, 2013).

Data collection forms the basis of most AI systems, where large amounts of data are gathered to train machine learning models. However, this data often includes personal information, the collection of which raises significant privacy concerns. Consent becomes a key issue in this regard, as it is necessary to obtain explicit permission from the individuals from whom data is collected. This may involve making users aware of what kind of data is being collected, how it is being collected, and for what purposes (Narayanan & Shmatikov, 2010).

Once data is collected, it's essential to regulate how it's used. Many AI applications involve processing personal data to deliver personalised services, which can pose risks to individual privacy if not appropriately managed. It's critical that the use of data aligns with the purpose for which it was collected. This also extends to situations where data is shared with third parties, requiring robust data usage policies and measures to protect privacy (Dwork, 2008).

The storage of collected data is another area where privacy issues emerge. Ensuring that stored data is secure from potential breaches is an ongoing challenge, requiring the implementation of robust data security measures. This includes encryption, secure databases, and secure data transmission protocols. In addition, data retention policies should be in place to determine how long data is stored and when it should be disposed of or anonymised to further protect privacy (Zyskind, Nathan & Pentland, 2015).

Emerging techniques like differential privacy offer promising ways to balance the utility of AI systems with privacy needs. Differential privacy involves adding noise to the data to prevent identification of individual records while still allowing useful patterns to be discerned (Dwork, 2008).

All of these factors underscore the importance of a strong privacy framework when dealing with AI systems. This not only involves technological solutions but also robust legal and ethical frameworks that ensure respect for individual privacy.

AI systems can also inadvertently perpetuate or exacerbate existing biases if they're trained on biased data. For instance, an AI algorithm used in hiring could potentially discriminate against certain demographic groups if the data it was trained on reflects past discriminatory hiring practices (Buolamwini & Gebru, 2018).

AI's decision-making processes are often opaque, leading to what is known as the 'black box' problem. This lack of transparency makes it difficult to determine why an AI made a particular decision, which complicates issues of accountability and trust. It's important for businesses to develop AI in a way that's explainable and transparent (Rudin, 2019).

AI can introduce new vulnerabilities into systems, making them potential targets for malicious actors. For instance, AI models can be manipulated through adversarial attacks, where small, purposeful changes to input data lead the model to make incorrect predictions. Businesses must prioritize robust security measures to protect their AI systems and data (Papernot et al., 2016).

Companies must consider ethics when designing and using AI. This involves respecting human rights, avoiding harm, ensuring fairness, and upholding transparency in AI applications. Many organizations are now implementing AI ethics guidelines and involving ethicists in their AI development processes to ensure responsible use of technology (Jobin, Ienca & Vayena, 2019).

The rapid evolution of AI has outpaced the development of related laws and regulations, creating a complex legal landscape. Businesses must be mindful of existing laws that may apply to their AI applications, such as data protection regulations, and also anticipate future regulatory shifts (Whittaker et al., 2018). Addressing these ethical and safety considerations is not just about risk management—it's also an opportunity for businesses to build trust with their stakeholders, gain competitive advantage, and ensure that their AI systems are used for societal benefit.

2.3. Theoretical Framework

The Unified Theory of Acceptance and Use of Technology (UTAUT) is a seminal theoretical framework proposed by Venkatesh et al. (2003) in response to the diverse and fragmented user acceptance theories that emerged in the field of information systems. This literature review traces the historical development, application, and revisions of the UTAUT theory.

Origins and Development of UTAUT

The Unified Theory of Acceptance and Use of Technology (UTAUT) was introduced by Venkatesh, Morris, Davis, and Davis in 2003 to provide a comprehensive model that explained user intentions and usage behavior towards information technology. Prior to UTAUT, numerous theories and models sought to explain these phenomena, including the Theory of Reasoned Action (TRA), Technology Acceptance Model (TAM), Motivational Model (MM), Theory of Planned Behavior (TPB), Combined TAM and TPB (C-TAM-TPB), Model of PC Utilization (MPCU), Innovation Diffusion Theory (IDT), and Social Cognitive Theory (SCT). Each of these theories had its merits but also limitations, leaving a scattered landscape of understanding (Venkatesh et al., 2003).

Venkatesh et al. (2003) recognized the need for a more integrated framework that could more holistically and accurately predict technology acceptance and usage. By comparing the aforementioned eight theories, they identified commonalities and synthesized these elements into a unified model. They also empirically tested this new model against the individual theories, finding UTAUT to be significantly superior in explaining the variance in intention to use and use of technology.

In UTAUT, the user acceptance and usage of technology are determined by four main constructs:

Performance Expectancy: This is the degree to which an individual believes that using the system will help in job performance. It is similar to perceived usefulness in TAM and extrinsic motivation in MM. Performance Expectancy, as one of the critical constructs in the Unified Theory of Acceptance and Use of Technology (UTAUT), refers to the extent to which an individual believes that using a particular system or technology will enhance their job performance (Venkatesh et al., 2003). This concept aligns with similar constructs from other theories, such as 'Perceived Usefulness' in the Technology Acceptance Model (TAM) and 'Extrinsic Motivation' in the Motivational Model (MM).

Performance expectancy is a crucial determinant of technology acceptance because individuals are generally more inclined to use a technology that they believe will help them perform tasks more efficiently or effectively. If the perceived benefits of using a system, such as increased productivity or improved quality of work, outweigh the perceived costs, such as time and effort required to learn the new system, then an individual is more likely to adopt and use that system.

From a marketing perspective, understanding and addressing performance expectancy can significantly impact the success of technology products or services. When marketing a new technology, it is crucial to clearly communicate its benefits and how it can improve potential users' job performance or productivity. This can be achieved through various marketing strategies, such as showcasing case studies that demonstrate how the technology has improved performance in similar settings, offering free trials that allow users to experience the benefits first-hand, or using clear and compelling messaging in advertising and promotional materials that highlight the technology's performance-enhancing features.

Moreover, it is also important for marketers to consider the role of user characteristics, such as experience and voluntariness of use, as moderators of performance expectancy. For example, experienced users might have higher performance expectancy as they are familiar with similar systems and can more easily understand the potential benefits of a new technology. On the other hand, users who perceive that the use of the technology is voluntary might have lower performance expectancy if they don't see the immediate benefits of adopting the new system.

In summary, performance expectancy plays a critical role in shaping an individual's intention to use a technology. By understanding this construct and its implications, marketers can more effectively promote their technology products or services, leading to higher acceptance and use.

Effort Expectancy: This refers to the perceived ease of use of the technology, akin to the construct of the same name in TAM. Effort Expectancy is a pivotal construct in the Unified Theory of Acceptance and Use of Technology (UTAUT) that revolves around the perceived ease of use associated with a technology or system (Venkatesh et al., 2003). This construct correlates with similar components present in the Technology Acceptance Model (TAM), where 'Perceived Ease of Use' also dictates technology acceptance.

The underlying concept is straightforward: if a technology is deemed effortless to understand and use, users are more likely to accept and adopt it. Consequently, the perceived complexity of a technology becomes a barrier to its adoption, emphasizing the importance of a user-friendly interface and intuitive functionality in system design.

Marketers, therefore, must foreground the simplicity of using the technology when communicating with potential users. Demonstrating user-friendly attributes of the technology and its ease of integration into existing processes can enhance users' effort expectancy. This can be executed through comprehensive tutorials, accessible user guides, demonstrations, or customer testimonials, emphasizing the minimal learning curve associated with the technology.

User experience (UX) design also plays a crucial role in this context. A UX design that is intuitively navigable and user-friendly significantly lowers the perceived effort associated with the technology, thereby elevating its acceptance. For instance, offering a personalized onboarding experience or providing a responsive customer support system can aid users in understanding the technology better, thereby improving the effort expectancy.

It is also noteworthy that the effect of effort expectancy on technology acceptance is moderated by user characteristics such as age, gender, experience, and voluntariness of use. For example, older users or those with less technological experience might find a new system more challenging to use, thus requiring additional support or training to improve their effort expectancy (Venkatesh et al., 2003).

In conclusion, understanding and catering to effort expectancy can significantly enhance technology acceptance, thereby driving the marketing strategies of technology products and services.

Social Influence: This is the extent to which individuals perceive that important others believe they should use the new system. It is a similar concept to subjective norm in TRA, TPB, and C-TAM-TPB. Social Influence, a central construct in the Unified Theory of Acceptance and Use of Technology (UTAUT), is defined as the degree to which an individual perceives that important others believe they should use the new system (Venkatesh et al., 2003). This construct is grounded in social psychology and draws from similar elements found in the Theory of Reasoned Action (TRA), the Theory of Planned Behavior (TPB), and the Combined TAM and TPB (C-TAM-TPB) where 'Subjective Norm' plays a similar role.

Social influence primarily reflects the impact of peers, superiors, influencers, and social networks on an individual's decision to accept and use a technology. The more an individual perceives the technology as accepted and recommended by others, especially by those they trust or respect, the more likely they are to use it themselves.

In a marketing context, social influence offers an opportunity to leverage these social factors to enhance product adoption. Techniques such as influencer endorsements, customer testimonials, social proof through case studies, and recommendations from industry leaders or experts can significantly impact potential users' perceptions of the technology. For instance, if a potential customer sees that industry leaders have successfully adopted and benefitted from the technology, they may be more likely to see it as a credible and beneficial solution.

The influence of these social factors can be even more impactful when taking into account the moderating effects of certain user characteristics. For example, research shows that social influence is more likely to impact women and older workers, as well as those with less experience with the technology or system (Venkatesh et al., 2003). Therefore, marketers targeting these demographics might want to particularly emphasize social proof and endorsements in their strategies.

Overall, social influence is a powerful construct that can shape technology acceptance and adoption, and understanding its role can significantly enhance marketing strategies and outcomes.

Facilitating Conditions: This refers to the degree to which an individual believes that an organizational and technical infrastructure exists to support the system use. This construct draws from similar ideas in TPB, MPCU, and IDT.

Moreover, UTAUT introduced four key moderators - gender, age, experience, and voluntariness of use - to the model, which affect the impact of the four core constructs on technology acceptance and use. Facilitating Conditions is a vital construct within the Unified Theory of Acceptance and Use of Technology (UTAUT). It represents the extent to which an individual believes that there is an organizational and technical infrastructure in place to support the use of the system (Venkatesh et al., 2003). This concept mirrors similar components in the Theory of Planned Behavior (TPB), the Model of PC Utilization (MPCU), and the Innovation Diffusion Theory (IDT).

Facilitating conditions cover various aspects, including the availability of resources, technical assistance, and adequate training to use the technology. It takes into account both the objective factors such as the presence of supporting technology and organizational infrastructure, as well as the subjective perception of support availability by the user.

In marketing, it's crucial to reassure potential users about the facilitating conditions that exist to support the technology's use. This reassurance can have a substantial effect on reducing perceived barriers to technology adoption. For instance, potential users might be more willing to try out new technology if they know that robust customer service and training resources are available, or if they are aware that the necessary hardware or software is compatible with their current systems.

A variety of marketing tactics can be employed to communicate these conditions effectively. These may include showcasing testimonials from customers who had positive experiences with customer support, providing comprehensive onboarding programs and training materials, or explicitly stating the technical requirements for the system and the support provided to meet these.

Moreover, the effect of facilitating conditions on technology acceptance can be moderated by user experience and voluntariness of use. Users with more experience with the technology might find fewer barriers to using it, while those who perceive the use of the technology as mandatory could also perceive higher facilitating conditions (Venkatesh et al., 2003).

In conclusion, ensuring and effectively communicating facilitating conditions is essential for encouraging technology acceptance, making it an essential consideration in the marketing of technology products and services.

In conclusion, the development of UTAUT was a significant milestone in technology acceptance research, consolidating previous theories into a unified and robust explanatory model (Venkatesh et al., 2003).

Application and Extensions of UTAUT

The Unified Theory of Acceptance and Use of Technology (UTAUT) model, since its inception, has been extensively employed across diverse technology adoption studies and has found broad applicability across different contexts and technologies (Venkatesh et al., 2003). Moreover, multiple extensions to the model have been proposed to enhance its predictive power and specificity to unique contexts.

One key application of UTAUT is in the field of healthcare, where it has been used to understand the adoption of health information technology by healthcare professionals and patients (Holden & Karsh, 2010). Similarly, in the context of education, the UTAUT model has been applied to understand the factors influencing the acceptance of e-learning systems among students and teachers (Al-Adwan, Al-Adwan, & Smedley, 2013).

While the original UTAUT model has demonstrated strong predictive power, various researchers have proposed extensions to the model to account for specific contexts or additional influencing factors. For instance, the UTAUT2 model, proposed by Venkatesh, Thong, and Xu (2012), extends the original model to a consumer context, introducing three additional constructs: hedonic motivation (the fun or pleasure derived from using a technology), price value (the perceived benefit of a technology relative to its cost), and habit (the extent to which people tend to perform behaviors automatically because of learning).

Similarly, other studies have integrated factors such as trust, anxiety, and personal innovativeness into the UTAUT framework to examine their influence on technology acceptance in specific contexts like online shopping or mobile banking (Alalwan, Dwivedi, Rana, & Williams, 2016).

In conclusion, while the UTAUT model provides a robust and comprehensive framework for understanding technology acceptance, its application and extension across different contexts have further enriched its value, allowing researchers and practitioners to gain more nuanced insights into technology acceptance behavior.

Summary

Artificial Intelligence (AI) has brought about a revolution in the field of marketing, redefining traditional marketing methods and creating new opportunities (Chaffey, 2020). AI's ability to analyze vast amounts of data and derive actionable insights has paved the way for highly personalized and customer-centric marketing approaches (Li & Karahanna, 2015).

AI's applications in marketing are vast and diverse. The advent of chatbots, for example, has revolutionized customer service by providing prompt responses to customer inquiries at any time of the day (Xu et al., 2021). AI also supports data-driven decision-making through predictive analytics, allowing marketers to anticipate customer needs and trends (Nguyen et al., 2020). Additionally, AI plays a key role in automating marketing processes, like email marketing and content curation, freeing up time for strategic tasks (Davenport et al., 2019).

Furthermore, AI has made significant strides in personalizing customer experiences. Through machine learning algorithms, businesses can deliver highly customized content, offers, and product recommendations to individual customers based on their unique behaviors and preferences (Huang & Rust, 2020). This level of personalization has proven to increase customer engagement and boost conversion rates (Kumar & Reinartz, 2012).

Despite the promising potential of AI in marketing, its adoption among businesses varies significantly. Studies have shown that perceptions and attitudes towards AI can greatly influence its adoption and use (Ransbotham et al., 2019).

Understanding the perceptions of marketing managers, who are key decision-makers in implementing AI technologies, can provide valuable insights into the factors influencing AI adoption in sales and marketing. Furthermore, it is necessary to examine potential barriers or concerns that managers might have, such as the implications of AI on job security, ethical considerations related to data privacy, or the perceived complexity of AI technologies (Bughin et al., 2018).

Exploring these factors could help identify strategies to improve the acceptance and effective use of AI in marketing. Moreover, it could shed light on the training and support needed for marketing professionals to comfortably navigate and utilize AI tools in their work. Given the rapidly evolving nature of AI and its growing impact on marketing, such a study could offer timely and crucial insights for businesses, educators, and policymakers.

Chapter 3: Methodology

3.1 Overview of the Research Problem

In the modern era, Artificial Intelligence (AI) is pervading various business sectors, revolutionizing operations, decision-making, and customer interaction mechanisms. Among these sectors, marketing stands as a primary benefactor, with AI promising remarkable improvements in customer personalization, prediction accuracy, process automation, and customer service (Davenport et al., 2019). However, the assimilation of AI in marketing practices is not homogeneous, and several organizations are yet to fully utilize its potential.

The decision to adopt and effectively employ AI in sales and marketing practices lies heavily with marketing managers, who are often the key orchestrators of marketing strategies and technological integrations (Nguyen et al., 2020). Nonetheless, several factors influence their perception and acceptance of AI, which in turn affects its implementation. These factors may include technical competency, perceived usefulness and ease of use, cost implications, ethical considerations, and fear of job loss, among others (Ransbotham et al., 2019).

While a substantial body of literature exists on the application of AI in marketing, less attention has been dedicated to understanding these factors that shape marketing managers' perception and their subsequent decisions to employ AI for sales and marketing (Chaffey, 2020). An exploration into these factors will not only help comprehend the varying rates of AI adoption in marketing but will also provide insights into the challenges, reservations, and needs of the marketing managers in this respect.

By filling this research gap, the study aims to offer practical recommendations for organizations, AI solution providers, and policymakers to facilitate smoother AI adoption in marketing practices, ensuring enhanced performance, competitiveness, and value generation in today's digitally-driven marketplace. Consequently, this research problem holds significant relevance and potential for contributing valuable insights to the field of marketing technology adoption.

3.2 Operationalization of Theoretical Constructs

To study the perceived impact of using AI for sales and marketing, I propose a theoretical model, underpinned by the basic premises Unified Theory of Acceptance and Use of Technology (UTAUT) *(Venkatesh et. al, 2003)*. Facilitating Condition, Peer Influence, Performance Expectancy, Effort Expectancy and behavioral intention (Dwivedi et. al, 2019; Rana et al., 2016) are the variables adopted from UTAUT.

The following operationalization of theoretical constructs from the Unified Theory of Acceptance and Use of Technology (UTAUT) model will be utilized in the study:

1. **Facilitating Condition**: This construct reflects the degree to which a marketing manager believes that their organization provides the technical and organizational support required for the adoption and effective use of AI in sales and marketing. The operationalization of this construct could include measures such as the availability of technical resources, training, and organizational readiness for AI adoption.
2. **Peer Influence**: This construct represents the influence of peers and social circles on a marketing manager's decision to adopt AI in their practices. Operationally, this could be measured by gauging the extent of AI adoption and use by the manager's colleagues, peers in the industry, or other individuals who significantly influence their professional decisions.
3. **Performance Expectancy**: This construct reflects the degree to which a marketing manager believes that employing AI in sales and marketing will enhance their job performance. This could be operationally measured through various indicators, such as

expected improvement in decision-making, sales forecasting, customer targeting, or any other marketing performance metrics relevant to the organization.

4. **Effort Expectancy**: This construct represents the perceived ease of use of AI technologies in marketing and sales. It could be operationalized by assessing the manager's perception of how easy it is to learn and use the AI tools, the intuitiveness of the user interface, or the complexity of the underlying technology.
5. **Behavioral Intention**: This construct refers to the marketing manager's intent to use AI in sales and marketing. This could be operationally measured through a self-reported measure of the manager's intention to use AI in their work, including their plans to use AI in the near future and their willingness to use AI even if it requires significant effort or learning.
6. **Use Behavior**: This construct, if included in the model, refers to the actual usage of AI in sales and marketing practices by the marketing manager. It can be operationalized by objectively measuring the use of AI tools in the manager's work, such as frequency, duration, or specific use cases of AI application.

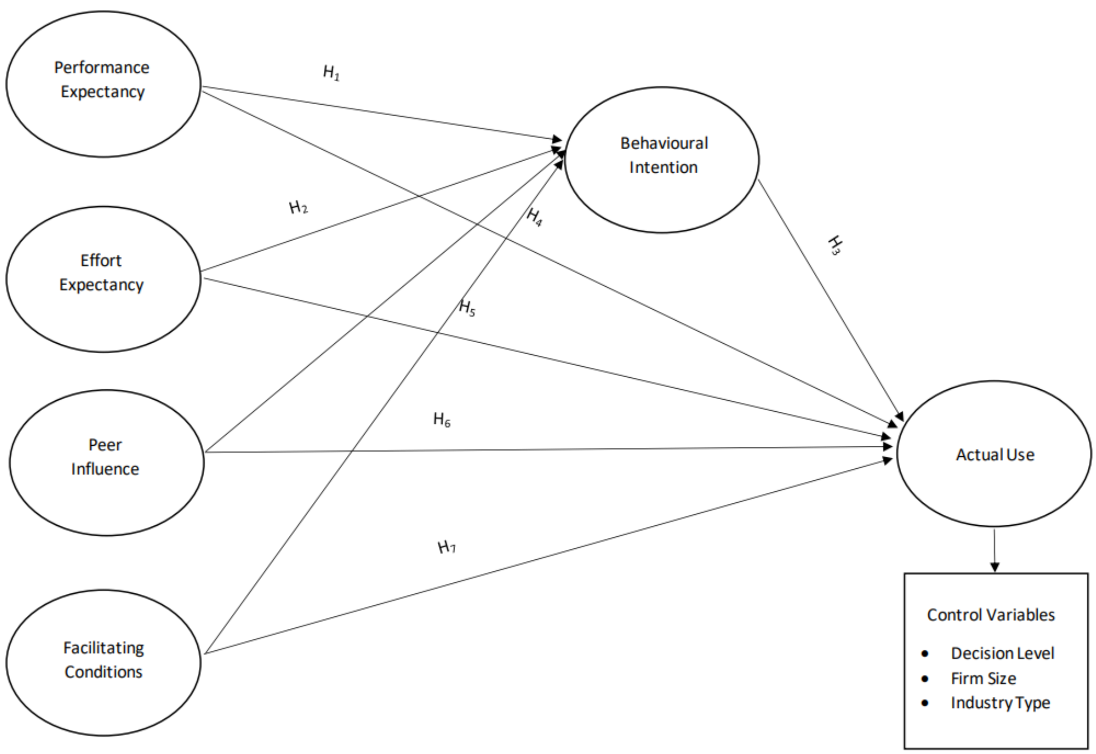
The operationalization of these constructs will require the design of appropriate measurement scales or the adaptation of existing, validated scales from previous research. The data collection could be facilitated through surveys or structured interviews, ensuring that each construct is thoroughly represented in the measurement instrument.

Variable Definition

- ***Actual Use:*** The marketing managers' use behaviour of AI for sales and marketing.
- ***Behavioural Intention:*** The degree of willingness of the marketing managers to use AI for sales and marketing.

- ***Performance Expectancy:*** The degree of belief of the marketing manager that using AI will help to achieve efficiency in Talent Acquisition.
- ***Effort Expectancy:*** The degree of ease associated with the use of AI for sales and marketing.
- ***Facilitating Condition:*** Marketing managers' belief about the infrastructure exists to support the use of AI for sales and marketing.
- ***Peer Influence:*** The degree which the marketing manager perceives that his industry peers believe he or she should use AI for sales and marketing.

Figure - 3.1: Theoretical Framework of the Study



Hypotheses of the Study

H_1 – Performance Expectancy will have a significant influence on the behavioral intention of the marketing managers towards the use of AI for sales and marketing

H_2 – Effort Expectancy will have significant influence on the behavioral intention of the marketing managers towards the use of AI for sales and marketing

H_3 – Peer Influence will have a significant influence on the behavioral intention to use AI for sales and marketing

H_4 - Facilitating Conditions will have significant influence on the behavioral intention to use AI for Talent Acquisition

H_5 – Performance Expectancy will have a significant influence on the actual use of AI for sales and marketing

H_6 – Effort Expectancy will have a significant influence on the actual use AI for sales and marketing

H_7 – Peer Influence will have a significant influence on the actual use of AI for sales and marketing

H_8 – Facilitating Conditions will have a significant influence on the actual use of AI for sales and marketing

H_9 – Behavioral Intention will have a significant influence on the actual use of AI for sales and marketing

3.3. Research Purpose and Questions

The purpose of this research is to gain a comprehensive understanding of marketing managers' perceptions and attitudes towards the employment of Artificial Intelligence (AI) in sales and marketing. This involves exploring their viewpoint on the effectiveness of AI, identifying factors that influence their behavioural intentions towards adopting AI, and assessing their perceptions of the impact of AI usage in their business practices. The research will contribute valuable insights for businesses, technology developers, and policy-makers, helping them better facilitate AI adoption in sales and marketing.

To achieve the aim of the study, the following research questions were framed.

1. What are the attitudes of marketing managers towards the effectiveness of using AI in sales and marketing?
2. What factors influence marketing managers' behavioural intentions towards using AI for sales and marketing?
3. How do marketing managers perceive the impact of using AI for sales and marketing on their business performance?

3.4 Research Design

The proposed research design follows a descriptive approach, which is fundamentally about "describing" the state of affairs as it exists. In this case, the research seeks to describe the relationships between the constructs of the Unified Theory of Acceptance and Use of Technology (UTAUT) in the context of marketing managers' perceptions and employment of AI in sales and marketing.

An empirical study will be undertaken to obtain data on these constructs - Facilitating Condition, Peer Influence, Performance Expectancy, Effort Expectancy, and Behavioral Intention - among a sample of marketing managers. This empirical data will help to provide a rich description of the current state of affairs regarding AI adoption in the marketing sector.

The relationships between these constructs will be examined using appropriate statistical analysis methods. For instance, the researchers might investigate how Facilitating Condition affects Behavioral Intention or how Performance Expectancy and Effort Expectancy together influence the actual Use Behavior. Through this, the research aims to highlight how these different factors interact and influence each other in the context of AI adoption in marketing.

Furthermore, descriptive research like this can provide a foundation for further exploratory or explanatory research. The relationships identified and described through this study could prompt more in-depth investigation into why these relationships exist, or how they could be leveraged to improve AI adoption in marketing.

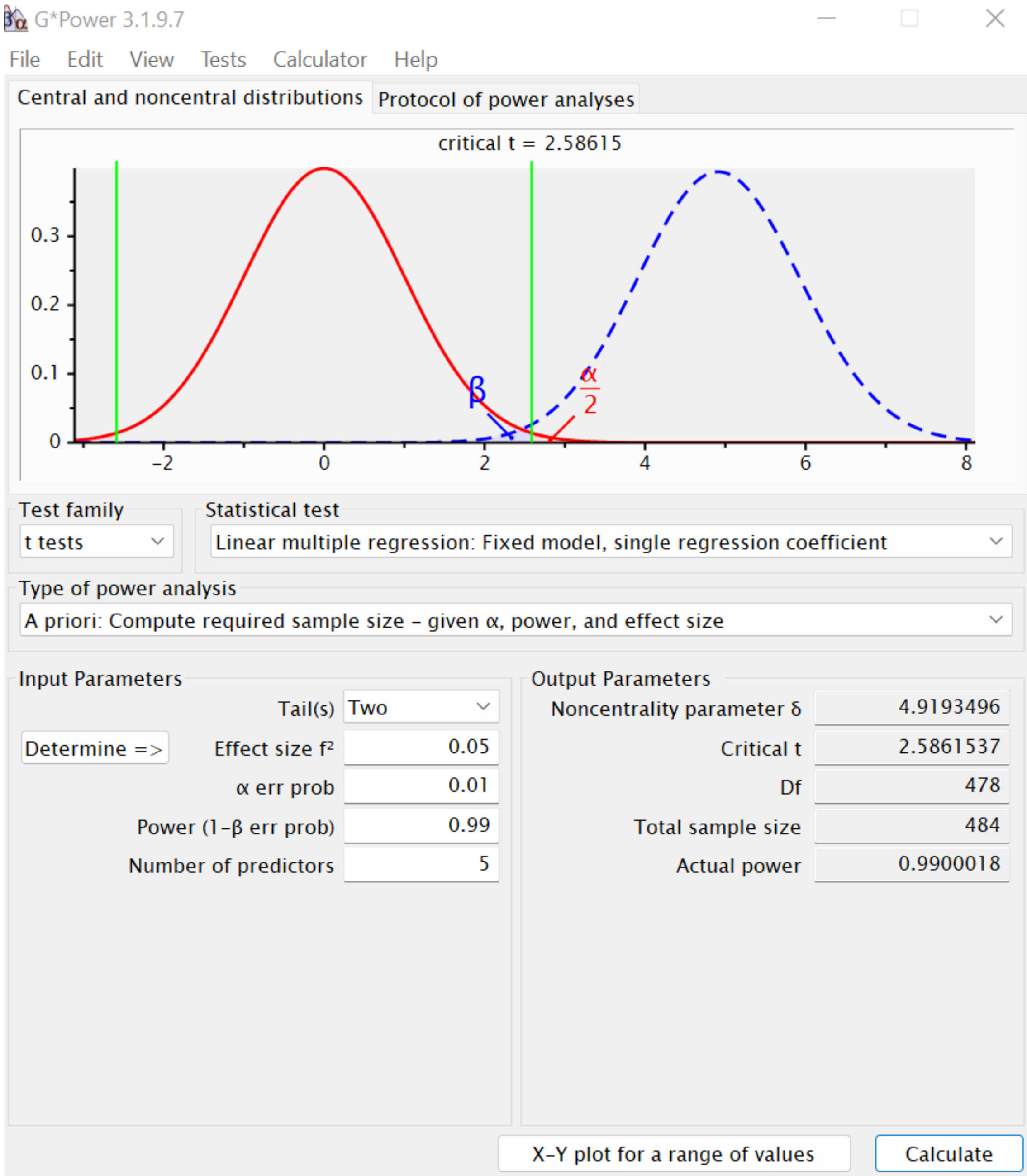
However, as this is a descriptive study, it's important to note that while it can highlight associations between the constructs, it does not imply causality. To investigate the cause-effect relationships, future research could consider adopting an experimental design.

The findings of this descriptive study will provide valuable insights for organizations, technology providers, and policymakers. By understanding the nature of the relationship between various factors affecting AI adoption in marketing, they can devise more effective strategies to promote AI acceptance and utilization, thereby reaping the associated benefits.

3.5 Population and Sample

G* Power software has been used to compute the required sample size needed for the proposed research model and the results of the software are shown in Figure -2.

Figure – 3.2: Minimum Sample Size



As the required sample size is 484, to ensure the statistical accuracy of the model and to reduce Type I and II errors, a sample size of 600 has been used for the study. I believe the increased sample size will ensure the robustness of the results.

3.6 Participant Selection

A purposive sampling technique is used for the study as the respondents must be aware of AI to answer the questionnaire.

3.7 Instrumentation

Measurement Scale

Please rate the Below Statements (From 1 – strongly disagree to 7 – strongly agree)

Construct	**Indicator**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Performance Expectancy *(Venkatesh et al., 2003)*	PE01 - AI tools significantly improve sales and marketing efficiency							
	PE02 - AI can effectively analyze and interpret complex data for sales and marketing							
	PEO3 - Using AI for sales and marketing will lead to better decision-making							
	PE04 - AI can help in identifying new sales and marketing opportunities e. AI contributes to increased sales and marketing effectiveness							
Effort Expectancy	EE01 - AI tools for sales and marketing are user-friendly							

(Venkatesh et al., 2003)	EE02 - Learning to use AI for sales and marketing is easy							
	EE03 - Implementing AI for sales and marketing tasks requires minimal effort							
	EE04 - The benefits of using AI for sales and marketing outweigh the effort required							
Facilitating Condition *(Venkatesh et al., 2003)*	FC01 - My organization provides the necessary resources to use AI for sales and marketing							
	FC02 - There is adequate support available to learn and use AI tools for sales and marketing							
	FC03 - Necessary infrastructure is in place to implement AI for sales and marketing							
Peer Influence *(Rana et al., 2016)*	PI01 - My peers in the industry regularly discuss the use of AI in sales and marketing.							
	PI02 - Colleagues in my network have adopted AI tools for sales and marketing.							

	PI03 - There is a strong peer consensus on the value of AI in sales and marketing.							
Behavioral Intention *(Dwivedi et al., 2019)*	BI01 - I intend to use AI tools for sales and marketing in the near future.							
	BI02 - I plan to increase my use of AI for sales and marketing tasks.							
	BI03 - I will actively seek opportunities to implement AI in sales and marketing.							
Actual Use *(Venkatesh et al., 2003)*	AU01 - I frequently use AI tools for sales and marketing tasks							
	AU02 - AI is an essential component of my sales and marketing strategy							
	AU03 - I actively explore and implement new AI technologies for sales and marketing							

3.8 Data Collection Procedures

The study is mainly based on primary data. The opinions of the respondents are collected using a well-structured and pre-tested questionnaire.

3.9 Data Analysis

Due to the complexity of the model, PLS-SEM analysis will be done using SMART PLS software.

Chapter 4: Results and Analysis

4.1 Assessment of Measurement Models

To ensure the quality and reliability of the measurement models used in this study, the guidelines provided by Hair et al. (2019) were followed. The indicators used in the study are reflective in nature, meaning that they are intended to measure a construct or concept. The assessment of reflective measurement models involves evaluating various aspects such as internal reliability, internal consistency, convergent validity, and discriminant validity.

Internal reliability refers to the consistency and stability of the indicators in measuring the underlying construct. In this study, internal reliability was assessed by examining the indicator loadings, which represent the strength of the relationship between each indicator and its corresponding construct. These indicator loadings are presented in Table 4.1, allowing for a comprehensive evaluation of the reliability of the measurement model.

In addition to internal reliability, other aspects such as internal consistency, convergent validity, and discriminant validity are also considered. Internal consistency examines the extent to which the indicators within a construct are highly correlated with each other. Convergent validity assesses the degree of agreement between different indicators measuring the same construct, indicating that they are converging on the same underlying concept. Discriminant validity, on the other hand, evaluates the extent to which different constructs are distinct from each other, indicating that they are measuring unique concepts.

By following the guidelines outlined by Hair et al. (2019) and considering these various aspects, the measurement models used in this study have been carefully evaluated to ensure their reliability and validity in measuring the intended constructs.

Table 4.1: Indicator Loadings

Construct	Item	Loading
Performance Expectancy	PE01	0.9
	PE02	0.836
	PE03	0.789
	PE04	0.933
Effort Expectancy	EE01	0.858
	EE02	0.89
	EE03	0.864
	EE04	0.891
Facilitating Condition	FC01	0.884
	FC02	0.897
	FC03	0.841
Peer Influence	PI01	0.891
	PI02	0.905
	PI03	0.859
Behavioral Intention	BI01	0.935
	BI02	0.856
	BI03	0.934
Actual Use	AU01	0.924
	AU02	0.855

	AU03	0.917

Source: *Primary Data*

Note: PLS-SEM analysis is done using SMART PLS software

Indicator loadings play a crucial role in assessing the reliability and validity of reflective measurement models. These loadings indicate the amount of variance shared between individual variables and the underlying construct they represent. By examining the indicator loadings, we can ensure the reliability of the indicators in measuring the construct.

In our study, Table 4.1 presents the indicator loadings for our measurement models. It is worth noting that all the indicator loadings surpass the recommended critical value of 0.708, as suggested by Hair et al. (2019). This critical value indicates that the associated construct explains more than 50% of the variance in the indicator, thus providing satisfactory indicator reliability. Consequently, we can conclude that our model demonstrates adequate indicator reliability.

Having established indicator reliability, the next step is to assess internal consistency and convergent validity. Composite reliability and ρA are used to evaluate the internal consistency of reflective constructs, while Average Variance Extracted (AVE) is employed to assess convergent validity. Table 4.2 displays the composite reliability, ρA, and AVE values for our assessment model.

Observing Table 4.2, we find that both the composite reliability and ρA fall within the recommended thresholds of 0.70 and 0.95. Moreover, all the AVE values exceed the critical threshold of 0.5. These results indicate that our reflective assessment model exhibits a satisfactory level of internal consistency and convergent validity.

In summary, by examining the indicator loadings, composite reliability, ρA, and AVE values, we have ensured the reliability, internal consistency, and convergent validity of our reflective measurement models. These assessments provide confidence in the robustness and validity of our research findings.

Table 4.2: Reliability and Validity

Constructs	**ρA**	**Composite Reliability**	**Average Variance Extracted**
Performance Expectancy	0.901	0.923	0.751
Effort Expectancy	0.905	0.929	0.767
Peer Influence	0.895	0.916	0.784
Facilitating Condition	0.856	0.907	0.764
Behavioral Intention	0.898	0.934	0.826
Actual Use	0.881	0.927	0.808

Source: *Primary Data*

Note: PLS-SEM analysis is done using SMART PLS software

The final step in evaluating the reflective measurement model is to ensure discriminant validity, which examines the degree to which each construct is distinct from other constructs in the model. Discriminant validity can be assessed using the Heterotrait-Monotrait (HTMT) ratio, which compares the correlations between different constructs to the correlations within the same construct. The HTMT values for our model are presented in Table 4.3.

Higher HTMT values indicate lower discriminant validity, suggesting a greater overlap between constructs. However, in our study, all the HTMT values for the reflective measurement model are significantly below the conservative threshold limit of 0.85.

Based on the findings presented in Table 4.3, we can confidently conclude that the discriminant validity of our model is satisfactorily established. The HTMT values indicate that the constructs in our model are distinct from one another and do not exhibit excessive overlap. This demonstrates that our measurement model effectively captures the unique aspects of each construct, ensuring the validity of our research results.

Table 4.2.3: Heterotrait-monotrait (HTMT) Ratio of Correlations

	Actual Use	**Behavioral Intention**	**Effort Expectancy**	**Facilitating Conditions**	**Peer Influence**
Behavioral Intention	0.654				
Effort Expectancy	0.526	0.786			
Facilitating Conditions	0.387	0.441	0.405		
Peer Influence	0.489	0.465	0.420	0.553	
Performance Expectancy	0.380	0.438	0.360	0.331	0.368

Source: *Primary Data*

Note: PLS-SEM analysis is done using SMART PLS software

4.2 Assessment of the Structural Model

The assessment of the structural model follows the guidelines provided by Hair et al. (2019). It involves three key aspects: examining collinearity issues, evaluating the relevance and significance of path coefficients, and assessing the explanatory and predictive power of the model. The results of our structural model are presented in Table 4.4, while the significance of the path coefficients and relevant hypotheses are depicted in Figure 4.1.

To address collinearity issues, the Variance Inflation Factor (VIF) is utilized. In Table 4.4, it can be observed that the VIF values are close to 3 or below. This indicates that collinearity is not at a critical level within the inner model, and it is unlikely to have a substantial impact on the regression results.

Next, we examine path coefficients' size and significance. With respect to control variables, decision level has significant impact on three constructs namely "effort expectancy ($\beta = 0.577$), facilitating condition ($\beta = 0.364$), and behavioral intention ($\beta = 0.285$)"; firm size has significant impact on four constructs namely "performanc expectancy ($\beta = -0.572$), effort expectancy ($\beta = -0.645$), facilitating condition ($\beta = -0.454$), and behavioral intention ($\beta = -0.196$)"; and industry type also has significant impact on four constructs namely "effort expectancy ($\beta = 0.496$), peer influence ($\beta = 0.576$), facilitating condition ($\beta = 0.355$), and behavioral intention ($\beta = 0.048$)". However, control variables don't have any significant impact on the endogenous construct (actual use) of the model.

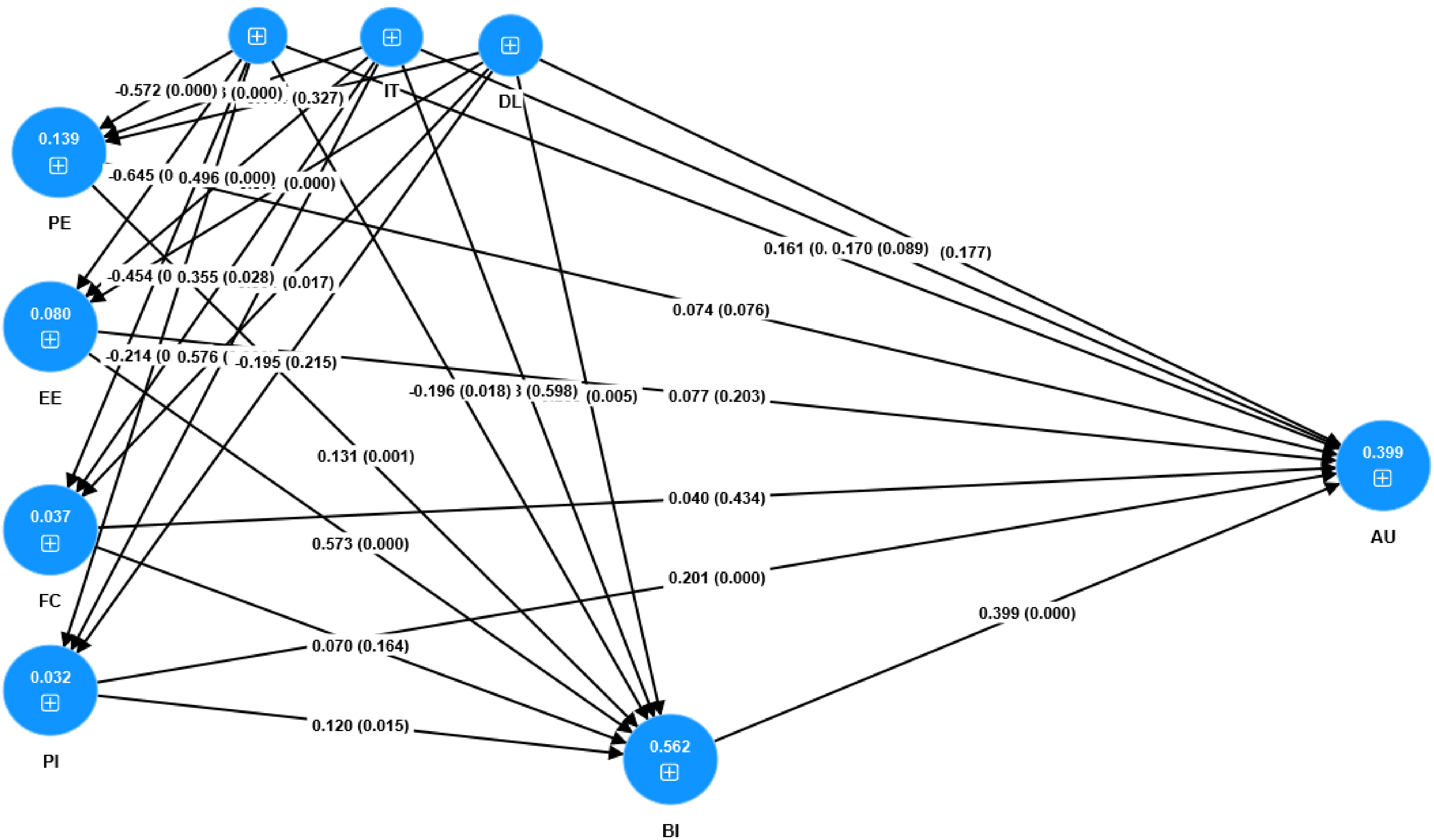
Figure 4.1 and Table 4.4 illustrates the size and significance of path coefficients between the endogenous and exogenous constructs. It can be seen from the figure and the table, that "performance expectancy ($\beta = 0.131$), effort expectancy ($\beta = 0.573$), and peer influence ($\beta = 0.12$)" has a significant positive correlation with behavioral intention. However, facilitating condition doesn't have any significant impact on behavioral intention.

On the other hand, "behavioral intention ($\beta = 0.399$), and peer influence ($\beta = 0.201$)" are the only two predictors have a significant positive impact on the endogenous construct (actual use) of the study.

An examination of the R^2 values in Table 4.4 reveals that performance expectancy, effort expectancy, and peer influence are important predictor constructs in explaining behavioral intention, with an R^2 value of 0.562. Additionally, behavioral intention and peer influence are significant predictor constructs in explaining actual use, with an R^2 value of 0.399. These results indicate that these constructs play a crucial role in influencing the behavior of individuals in relation to the use of AI marketing.

The R^2 value, being between 0.25 and 0.50, suggests that the model has achieved a moderate level of success (Hair et al., 2019) in explaining the factors that impact the actual use of AI marketing. It is noteworthy that effort expectancy has the largest f^2 effect size among the predictor constructs, with a value of 0.56, followed by behavioral intention with an f^2 value of 0.116. These effect sizes indicate the magnitude of the impact of these constructs on the outcome variable.

Figure 4.1: Structural Model Results



Note: *In the above structural model, Firm Size, Industry Type and Decision Levels have been considered as control variables.*

Table 4.4: Structural Model Results

Outcome	R Sq.	Predictor	Direct Paths & Hypotheses	β	CI	Significance?	f^2	VIF
Performance Expectancy	0.139	CV	Decision Level -> Performance Expectancy	-0.144	[-0.429; 0.145]	No	0.002	3.187
		CV	Firm Size -> Performance Expectancy	-0.572	[-0.804; -0.330]	Yes	0.038	2.455
		CV	Industry Type -> Performance Expectancy	0.163	[-0.372; 0.124]	No	0.123	1.732
Effort Expectancy	0.08	CV	Decision Level -> Effort Expectancy	0.577	[0.274; 0.874]	Yes	0.024	3.187
		CV	Firm Size -> Effort Expectancy	-0.645	[-0.863; -0.412]	Yes	0.045	2.455
		CV	Industry Type -> Effort Expectancy	0.496	[0.247; 0.743]	Yes	0.021	1.732
Peer	0.032	CV	Decision Level -> Peer	-0.195	[-0.502;	No	0.00	3.187

Influence			Influence		0.114]		3	
		CV	Firm Size -> Peer Influence	-0.214	[-0.448; 0.023]	No	0.005	2.455
		CV	Industry Type -> Peer Influence	0.576	[0.278; 0.864]	Yes	0.027	1.732
Facilitating Condition	0.037	CV	Decision Level -> Facilitating Condition	0.364	[0.063; 0.659]	Yes	0.009	3.187
		CV	Firm Size -> Facilitating Condition	-0.454	[-0.637; -0.272]	Yes	0.021	2.455
		CV	Industry Type -> Facilitating Condition	0.355	[0.038; 0.670]	Yes	0.01	1.732
Behavioral Intention	0.562	PE	Performance Expectancy -> Behavioral Intention	0.131	[0.059; 0.209]	Yes	0.03	1.325
		EE	Effort Expectancy -> Behavioral Intention	0.573	[0.489; 0.654]	Yes	0.56	1.337

		PI	Peer Influence -> Behavioral Intention	0.12	[0.024; 0.219]	Yes	0.023	1.45
		FC	Facilitating Condition -> Behavioral Intention	0.07	[-0.028; 0.169]	No	0.008	1.397
		CV	Decision Level -> Behavioral Intention	0.285	[0.089; 0.489]	Yes	0.012	3.362
		CV	Firm Size -> Behavioral Intention	-0.196	[-0.358; -0.029]	Yes	0.008	2.635
		CV	Industry Type -> Behavioral Intention	0.048	[0.247; 0.743]	Yes	0	1.955
Actual Use	0.399	PE	Performance Expectancy -> Actual Use	0.074	[-0.008; 0.156]	No	0.007	1.365
		EE	Effort Expectancy -> Actual Use	0.077	[-0.04; 0.195]	No	0.005	2.086
		PI	Peer Influence -> Actual Use	0.201	[0.088; 0.313]	Yes	0.045	1.482

		FC	Facilitating Condition -> Actual Use	0.04	[-0.062; 0.139]	No	0.002	1.409
		BI	Behavioral Intention -> Actual Use	0.399	[0.263; 0.540]	Yes	0.116	2.281
		CV	Decision Level -> Actual Use	-0.211	[-0.518; 0.093]	No	0.005	3.402
		CV	Firm Size -> Actual Use	0.161	[0.096; 0.438]	No	0.004	2.656
		CV	Industry Type -> Actual Use	0.17	[-0.029; 0.372]	No	0.003	1.956

Source: *Primary Data*

Note: PLS-SEM analysis is done using SMART PLS software

CI = 95% bootstrap two-tailed confidence interval, CV = Control Variable, PE = Performance Expectancy, EE = Effort Expectancy, FC = Facilitating Conditions, PI = Peer Influence, BI – Behavioral Intention.

4.3 Mediation Analysis

The significance and strength of the mediating constructs have been assessed using bootstrapping procedure at 95% confidence interval and the results are shown in Table 4.2.5.

Table 4.5: Structural Mediation

Path	**β**	**CI**	**Significance?**
Performance Expectancy -> Behavioral Intention -> Actual Use	0.052	[0.021; 0.094]	Yes
Effort Expectancy -> Behavioral Intention -> Actual Use	0.228	[0.148; 0.321]	Yes
Facilitating Conditions -> Behavioral Intention -> Actual Use	0.028	[-0.011; 0.074]	No
Peer Influence -> Behavioral Intention -> Actual Use	0.048	[0.009; 0095]	Yes

Source: *Primary Data*

Note: *PLS-SEM analysis is done using SMART PLS software*

CI = 95% bootstrap two-tailed confidence interval

It can be seen from the abvoe table, that "performance expectancy (β = 0.052), and peer influence (β = 0.048) have significant smaller positive impact on actual use via behavioral intention and effort expectancy (β = 0.228) has significant larger positive impact on actual use via behavioral intention". Facilitating condition doesn't have any significant mediating impact on actual use via behavioral intention.

4.4 Predict Relevance of the Model

The Q^2 values obtained for the major constructs using blindfolding technique are presented in Table 4.6. Q^2 measures the predictive relevance of the model and indicates how well the model can predict future outcomes.

From Table 4.6, it can be observed that all the Q^2 values are positive, indicating that the model has predictive power and can effectively predict the outcomes of the constructs. This suggests that the model is reliable and robust, as it demonstrates good predictive performance beyond the data used to develop the model.

The positive Q^2 values provide evidence that the model has out-of-sample predictive relevance and can be applied to new data or future scenarios. This further strengthens the confidence in the model's ability to explain and predict the factors influencing the actual use of AI in marketing.

Table 4.6: Predict Relevance of the Model

Construct	Q^2 Predict
Behavioral Intention	0.453
Actual Use	0.310

Source: *Primary Data*

Note: *PLS-SEM analysis is done using SMART PLS software*

Indeed, the Q^2 predict values in Table 4.6 are above zero, indicating that the model's predictions surpass the most basic benchmark, which is the indicator means from the analysis sample. The Q^2 predict values serve as a measure of the model's out-of-sample predictive relevance and demonstrate its ability to make predictions that outperform a simple average of the observed data.

By surpassing the benchmark, the model shows that it can provide valuable insights and predictions beyond what would be expected based solely on the average values of the observed data. This confirms the model's ability to generalize and make accurate predictions in real-world scenarios, enhancing its practical applicability and usefulness in understanding the factors influencing the actual use of AI in marketing.

4.5 Importance-Performance Map Analysis (IMPA)

From the results presented in Table 4.7 and Figure 4.2, it is evident that behavioral intention, effort expectancy, and peer influence have the largest total effects and are crucial in explaining the actual use of AI in marketing. These constructs exhibit significant impact and performance in relation to the endogenous construct, behavioral intention, as indicated by their respective total effects (behavioral intention - 0.393, effort expectancy - 0.308, peer influence - 0.250). Furthermore, the performance scores associated with these constructs reinforce their importance in driving the actual use of AI in marketing. Notably, behavioral intention shows the highest performance score (48.495), followed by effort expectancy (48.045) and peer influence (0.250). These constructs have above-average performance levels, indicating their significant influence on the endogenous construct.

On the other hand, performance expectancy and facilitating condition exhibit smaller total effects compared to the previously mentioned constructs. Their respective total effects (performance expectancy - 0.138, facilitating condition - 0.067) suggest a relatively lower impact on the actual use of AI in marketing. This is supported by their performance scores, which fall below the average level (performance expectancy - 43.595, facilitating condition - 45.170).

Indeed, based on the IMPA analysis, it is evident that the performance of behavioral intention has the highest impact on the actual use of AI in marketing. The findings suggest that a 1 unit increase in the performance of behavioral intention, such as from 48.498 to 49.495, leads to a corresponding increase in the actual use of AI in marketing, from 49.834 to 50.227. This signifies that behavioral intention plays a crucial and influential role in driving the adoption and utilization of AI in marketing practices. The results highlight the importance of promoting and enhancing behavioral intention as a key factor in achieving the desired outcome of increased actual use of AI in marketing.

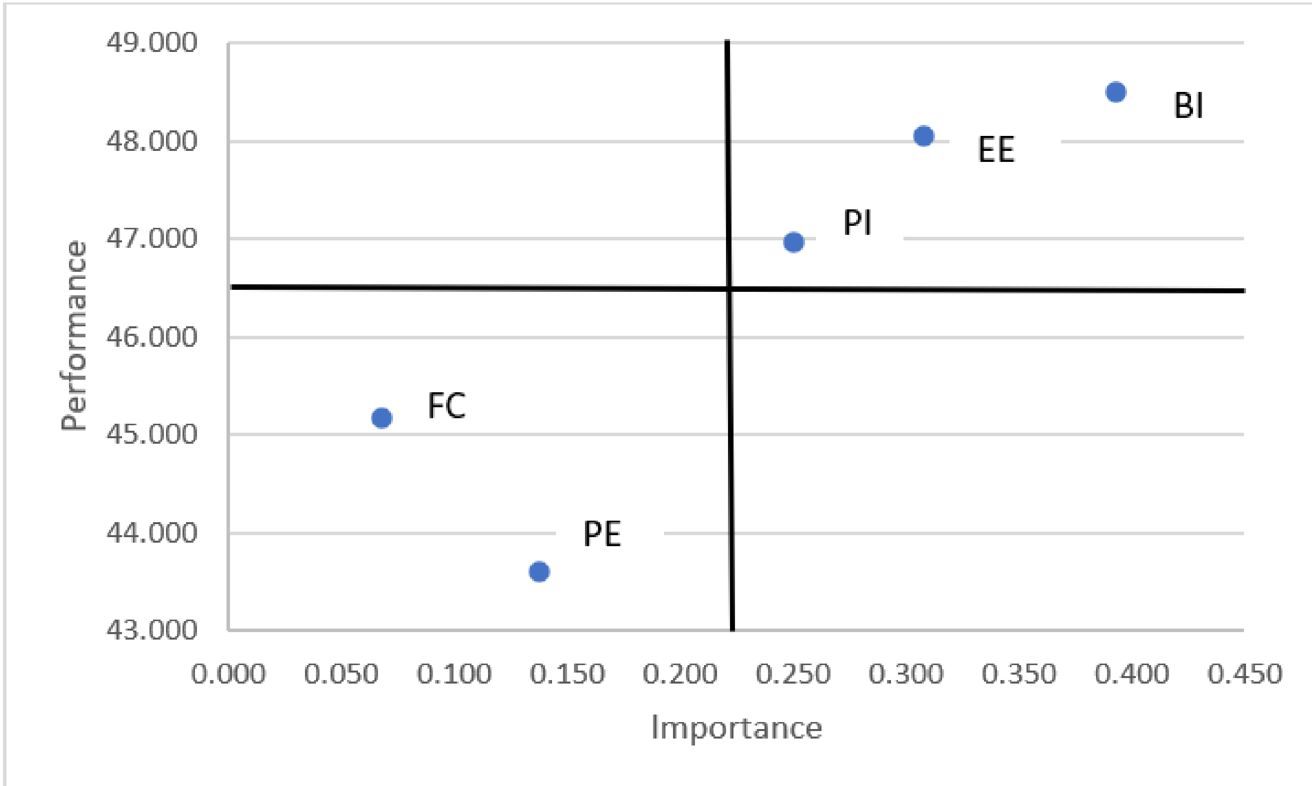
Table 4.7: Importance-Performance Map Analysis

	Unstandardized Total Effect	**Performance**	**LV Performance**
Behavioral Intention	0.393	48.495	-
Effort Expectancy	0.308	48.045	-
Facilitating Condition	0.067	45.170	-
Peer Influence	0.250	46.955	-
Performance Expectancy	0.138	43.595	-
Actual Use	-	-	49.834
Average	0.231	46.452	

Source: *Primary Data*

Note: PLS-SEM analysis is done using SMART PLS software

Figure: 4.2: Importance-Performance Map Analysis



Note: *PE = Performance Expectancy, EE = Effort Expectancy, FC = Facilitating Conditions, PI = Peer Influence, BI = Behavioral Intention.*

Chapter 5: Discussion

5.1 Predictors affecting the Behavioral Intention of using AI in Sales and Marketing

The study finds that performance expectancy, effort expectancy and peer influence are the major predictors affecting the intention to use AI in sales and marketing. The study's findings on the role of performance expectancy, effort expectancy, and peer influence in marketing managers' behavioral intention to adopt AI in sales and marketing is supported by ample literature (Venkatesh et al., 2003; Liu et al., 2020; Xu & Syam, 2021; Davenport & Ronanki, 2018; Kumar & Sharma, 2021; Huang & Rust, 2021; Bughin et al., 2017).

Performance Expectancy

Performance expectancy refers to the degree to which an individual believes that using a particular technology will enhance their job performance (Venkatesh et al., 2003). In the context of AI in sales and marketing, research has shown that AI technologies can improve the efficiency and effectiveness of marketing campaigns (Liu et al., 2020). Moreover, AI-driven marketing systems have been proven to increase return on investment, customer engagement, and conversion rates (Xu & Syam, 2021). These results support the study's findings that marketing managers' performance expectancy plays a role in their intention to adopt AI technologies. In the context of AI in sales and marketing, this belief can be crucial in determining the intention to adopt AI-driven technologies.

AI has been shown to offer various benefits to sales and marketing functions, such as enhancing data-driven decision-making and providing personalized experiences to customers (Nguyen et al., 2020). By leveraging vast amounts of data, AI can identify patterns and trends that help marketing managers make more informed decisions and target customers with more precision (Chui et al., 2018). This increased accuracy can lead to higher conversion rates and customer satisfaction, which in turn contribute to better overall performance (Sivarajah et al., 2017).

Furthermore, AI-powered marketing tools can automate repetitive tasks, allowing marketers to allocate their time and resources more efficiently (Kumar et al., 2019). As a result, marketing managers who believe in the potential of AI to improve their job performance are more likely to adopt AI technologies (Edeling & Fischer, 2020).

Several studies have found a strong positive relationship between performance expectancy and the intention to use AI in sales and marketing. For instance, a study by Gangwar et al. (2015) discovered that performance expectancy was the most significant predictor of technology adoption in a business context. Similarly, a study by Tarhini et al. (2017) found that performance expectancy was an important factor influencing the adoption of innovative technologies among marketing professionals.

Performance expectancy plays a pivotal role in shaping marketing managers' intentions to use AI in sales and marketing, as it reflects their beliefs in the technology's potential to improve their job performance (Venkatesh et al., 2003; Nguyen et al., 2020; Chui et al., 2018; Sivarajah et al., 2017; Kumar et al., 2019; Edeling & Fischer, 2020; Gangwar et al., 2015; Tarhini et al., 2017). Further, the impact of performance expectancy on the intention to use AI in sales and marketing is also supported by the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Davis, 1989; Venkatesh et al., 2003). Both frameworks emphasize the role of perceived usefulness or performance expectancy as a significant factor influencing technology adoption.

Moreover, studies have shown that AI can help marketing managers in areas such as customer segmentation, product recommendation, and price optimization (Kapoor et al., 2018). These AI-driven applications can facilitate the personalization of marketing messages and offers, ultimately leading to improved customer experiences and increased loyalty (Li et al., 2018). As marketing managers become aware of the potential benefits of AI, their performance expectancy is likely to increase, resulting in a higher intention to adopt AI in sales and marketing (Marr, 2018).

It is important to note that the relationship between performance expectancy and intention to use AI in sales and marketing may be influenced by external factors such as organizational culture, technological infrastructure, and the level of AI understanding within the organization (Bharadwaj & Noble, 2020). These factors can either facilitate or hinder the adoption of AI, depending on how they align with the perceived benefits of AI-driven technologies (Hong et al., 2020). The potential benefits of using AI in sales and marketing are numerous and varied, as the technology can improve various aspects of these domains. Some key benefits include:

- Enhanced data analysis: AI can process and analyze vast amounts of data more quickly and accurately than humans, allowing marketers to identify patterns, trends, and insights that help make more informed decisions and create more effective strategies (Chui et al., 2018).
- Personalization: AI can analyze customer data, such as browsing history, preferences, and purchase behavior, to create highly personalized marketing messages and offers. This, in turn, can lead to improved customer experiences, increased engagement, and higher conversion rates (Li et al., 2018).
- Customer segmentation: AI can automatically segment customers based on their behavior, preferences, and demographics, enabling marketers to target their campaigns more effectively and efficiently (Kapoor et al., 2018).
- Automation of repetitive tasks: AI can handle routine and repetitive tasks, such as data entry, email marketing, and social media management, freeing up marketing

professionals to focus on more strategic and creative initiatives (Kumar et al., 2019).

- Improved customer service: AI-powered chatbots and virtual assistants can provide instant, accurate, and personalized customer support, increasing customer satisfaction and loyalty (Huang & Rust, 2021).
- Product recommendations: AI algorithms can analyze customer behavior and preferences to suggest relevant products or services, resulting in higher sales and better customer experiences (Nguyen et al., 2020).
- Price optimization: AI can dynamically adjust pricing based on factors such as demand, competition, and customer behavior, maximizing revenue and profit (Chen et al., 2019).
- Forecasting and predictive analytics: AI can predict future trends, customer behaviors, and market conditions, enabling marketers to make more informed decisions and plan proactively (Sivarajah et al., 2017).
- Content creation and optimization: AI can generate marketing content, such as email subject lines, social media posts, and ad copy, as well as optimize existing content for better search engine performance and user engagement (Edeling & Fischer, 2020).
- Performance tracking and optimization: AI can continuously monitor and analyze the performance of marketing campaigns, providing real-time insights and suggestions for improvement, ultimately leading to better return on investment (ROI) (Bughin et al., 2017).

These benefits demonstrate the significant potential of AI in revolutionizing sales and marketing practices, making it a valuable tool for organizations looking to enhance their performance and stay competitive in the rapidly evolving digital landscape.

Effort Expectancy

Effort expectancy represents the perceived ease of use associated with adopting a particular technology (Venkatesh et al., 2003). In the case of AI in sales and marketing, the intuitive nature and user-friendly interfaces of AI-driven marketing tools can encourage adoption (Davenport & Ronanki, 2018). Additionally, AI systems often provide marketers with actionable insights, simplifying the decision-making process (Kumar & Sharma, 2021). This ease of use can lead to increased effort expectancy, contributing to the study's findings on the importance of this factor in AI adoption.

A higher effort expectancy indicates that marketing managers believe AI-driven tools will be user-friendly, easy to learn, and not overly complex to use, making them more likely to adopt these technologies (Venkatesh & Davis, 2000). The impact of effort expectancy on the intention to use AI in sales and marketing can be explained by the Technology Acceptance Model (TAM), which posits that perceived ease of use, along with perceived usefulness, is a key determinant of technology adoption (Davis, 1989). According to TAM, if marketing managers perceive that AI tools are easy to use, they are more likely to integrate them into their daily operations, as they expect the technology to reduce their workload and improve their performance (Ma & Liu, 2004).

Research has shown that AI-driven marketing tools with user-friendly interfaces and intuitive features can encourage adoption among marketing managers. For instance, AI-powered platforms often provide marketers with actionable insights and recommendations, simplifying the decision-making process and making it easier for them to leverage the technology (Kumar & Sharma, 2021). Moreover, as AI tools become more advanced, they increasingly incorporate features designed to minimize the learning curve and reduce the complexity of use (Davenport & Ronanki, 2018).

Studies have found a positive relationship between effort expectancy and the intention to adopt AI in sales and marketing. For example, a study by Wu and Chen (2017) demonstrated that effort expectancy was a significant predictor of technology adoption among marketing professionals. Similarly, Tarhini et al. (2017) found that effort expectancy had a positive impact on the intention to use innovative technologies in a marketing context. It is proved that effort expectancy plays a crucial role in shaping marketing managers' intentions to use AI in sales and marketing, as it influences their beliefs about the ease of use and potential workload reduction associated with adopting AI-driven tools (Venkatesh et al., 2003; Venkatesh & Davis, 2000; Davis, 1989; Ma & Liu, 2004; Kumar & Sharma, 2021; Davenport & Ronanki, 2018; Wu & Chen, 2017; Tarhini et al., 2017). However, improving the perception of marketing managers regarding effort expectancy in using AI for sales and marketing can be challenging due to various factors. Some of these challenges include:

- Complexity of AI technologies: AI systems can be complex and difficult to understand for non-technical marketing managers. This complexity might lead to the perception that AI tools are difficult to use, which can discourage adoption (Davenport & Ronanki, 2018).
- Lack of familiarity with AI: Marketing managers who are not familiar with AI concepts and technologies may perceive the learning curve as steep, making them less likely to adopt AI-driven tools in their marketing efforts (Tarhini et al., 2017).
- Insufficient training and support: A lack of adequate training and support can hinder marketing managers' confidence in using AI for sales and marketing. Organizations need to provide comprehensive training and ongoing support to help marketing

managers develop the skills and knowledge necessary to effectively use AI tools (Kelleher & Tierney, 2018).

- Resistance to change: Marketing managers who are used to traditional marketing methods may be resistant to adopting new technologies, including AI. This resistance can stem from fear of job displacement or a preference for established practices (Bughin et al., 2017).
- Integration challenges: Integrating AI-driven tools with existing marketing systems and processes can be complex and time-consuming. Marketing managers might perceive this integration as a significant effort, which could negatively impact their effort expectancy (Nguyen et al., 2020).
- Usability issues: AI tools that have poor user interfaces or are difficult to navigate can create a negative perception of effort expectancy. Developers need to prioritize usability when designing AI tools to ensure that they are user-friendly and intuitive for marketing managers (Venkatesh et al., 2003).
- Concerns about data privacy and security: Marketing managers may be hesitant to adopt AI tools due to concerns about data privacy and security, particularly when handling sensitive customer information. Addressing these concerns and ensuring that AI tools meet data protection standards is crucial for improving effort expectancy (Li et al., 2018).

To overcome the challenges associated with improving marketing managers' perception of effort expectancy when using AI for sales and marketing, organizations can implement the following strategies:

- Education and awareness: Educate marketing managers about AI concepts, technologies, and applications to demystify the complexities and facilitate better understanding. This can be achieved through seminars, workshops, or online courses (Davenport & Ronanki, 2018).

- Comprehensive training programs: Develop and provide in-depth training programs to teach marketing managers how to use AI-driven tools effectively. Tailor the training to different skill levels and ensure that it covers both technical and practical aspects (Kelleher & Tierney, 2018).
- Ongoing support: Offer ongoing support to marketing managers as they adopt AI tools. This can include access to knowledgeable personnel, regular check-ins, and updates on the latest AI advancements in sales and marketing (Nguyen et al., 2020).
- Change management: Implement a well-structured change management strategy that addresses potential resistance to AI adoption. This may involve communicating the benefits of AI, involving marketing managers in the decision-making process, and providing reassurance about job security (Bughin et al., 2017).
- Seamless integration: Choose AI tools that can be easily integrated with existing marketing systems and processes. This will minimize disruption and reduce the perceived effort involved in adopting the new technology (Venkatesh et al., 2003).
- Usability and user experience: Prioritize AI tools with intuitive, user-friendly interfaces to encourage adoption among marketing managers. Work closely with developers to ensure that the tools are easy to navigate and meet the needs of the marketing team (Venkatesh & Davis, 2000).
- Data privacy and security: Address concerns about data privacy and security by ensuring that AI tools comply with data protection regulations and industry best practices. Clearly communicate the steps taken to protect sensitive customer information and maintain transparency in data usage (Li et al., 2018).

- Demonstrating success: Share case studies and success stories of AI adoption in sales and marketing to showcase the potential benefits and build confidence among marketing managers. Highlighting the positive impact of AI on other organizations can motivate marketing managers to embrace the technology (Tarhini et al., 2017).
- Encourage collaboration: Promote collaboration between marketing managers and data scientists or AI specialists to facilitate knowledge sharing, foster understanding, and build trust in AI technologies (Davenport & Ronanki, 2018).
- Gradual implementation: Introduce AI tools incrementally, starting with simpler applications before moving on to more complex ones. This gradual approach can help marketing managers become more comfortable with the technology and gain confidence in their ability to use it effectively (Kumar & Sharma, 2021).

By implementing these strategies, organizations can overcome the challenges associated with improving marketing managers' perception of effort expectancy and increase the likelihood of AI adoption in sales and marketing.

Peer Influence

Peer influence, or social influence, reflects the extent to which an individual perceives that important others believe they should adopt a particular technology (Venkatesh et al., 2003). In the realm of AI for sales and marketing, the adoption of AI-driven tools has been widely discussed and praised by industry leaders and experts (Huang & Rust, 2021). This positive discourse can influence marketing managers' perceptions of the technology and their likelihood to adopt it (Bughin et al., 2017). Therefore, the study's identification of peer influence as a crucial factor in AI adoption aligns with existing research.

Peer influence can serve as a powerful motivator for technology adoption, as individuals are more likely to adopt new technologies when they observe others using and benefiting from them (Rogers, 2003). The impact of peer influence on the intention to use AI in sales and marketing can be explained through the Social Influence Theory and the Diffusion of Innovations Theory. According to the Social Influence Theory, individuals are more likely to adopt a new technology when they perceive that important others, such as colleagues and industry peers, approve of its use and expect them to use it (Fishbein & Ajzen, 1975). Similarly, the Diffusion of Innovations Theory posits that the adoption of new technologies is influenced by the extent to which they are adopted and endorsed by others within a social network (Rogers, 2003).

Empirical research has demonstrated the impact of peer influence on the intention to use AI in sales and marketing. For instance, a study by Kim and Kankanhalli (2009) found that peer influence significantly influenced individuals' intentions to adopt AI-driven marketing tools. Similarly, Wu and Chen (2017) demonstrated that social influence was a significant predictor of technology adoption among marketing professionals.

In the context of AI adoption in sales and marketing, marketing managers may be influenced by the successes and experiences of other organizations or colleagues who have integrated AI into their marketing strategies (Huang & Rust, 2021). Positive experiences shared by peers can help alleviate fears, build trust in the technology, and demonstrate the potential benefits of AI, ultimately increasing the likelihood of adoption (Bughin et al., 2017).

To maximize the positive impact of peer influence, Companies can increase peer influence with respect to the use of AI in sales and marketing through various strategies:

- Success stories and case studies: Share success stories and case studies of AI implementation in sales and marketing, both internally and externally. Showcasing the positive impact of AI on other organizations can motivate marketing managers to embrace the technology (Davenport & Ronanki, 2018).

- Networking events and conferences: Organize and encourage attendance at industry events, conferences, and workshops related to AI in sales and marketing. These events facilitate networking with industry professionals who have successfully implemented AI, providing firsthand insights and fostering peer influence (Kumar & Sharma, 2021).
- Collaborative projects: Encourage collaboration between marketing teams or departments that have already adopted AI and those who are considering it. This can promote knowledge sharing and help build trust in AI technologies (Nguyen et al., 2020).
- Industry partnerships: Develop partnerships with other organizations or industry associations to jointly promote AI adoption in sales and marketing. Collaborative initiatives can create a sense of community and encourage shared learning (Bughin et al., 2017).
- Internal champions: Identify and empower internal champions who are enthusiastic about AI and can advocate for its adoption within the organization. These champions can help drive positive peer influence by sharing their experiences and successes with colleagues (Davenport & Ronanki, 2018).
- Training and mentorship programs: Establish training and mentorship programs that involve experienced AI users guiding and supporting those who are new to the technology. This can foster peer influence by demonstrating the value and potential benefits of AI adoption in sales and marketing (Kelleher & Tierney, 2018).
- Recognition and rewards: Recognize and reward employees who successfully adopt and implement AI in sales and marketing. This can incentivize others to follow suit

and can create a culture that embraces AI adoption (Venkatesh et al., 2003).

- Social media and online forums: Encourage participation in online forums, social media groups, and industry-specific platforms where marketing managers can share their AI experiences and learn from their peers. This can foster a sense of community and enhance peer influence (Wu & Chen, 2017).
- Testimonials and endorsements: Obtain and share testimonials and endorsements from industry influencers and respected professionals who have successfully adopted AI in sales and marketing. This can help build credibility and encourage others to adopt AI (Rogers, 2003).
- Pilot programs: Implement pilot programs that allow marketing managers to test AI tools and share their experiences with peers. Successful pilot programs can generate positive peer influence and encourage wider adoption (Kumar & Sharma, 2021).

By implementing these strategies, companies can increase peer influence with respect to the use of AI in sales and marketing, ultimately fostering a positive environment for AI adoption. In summary, peer influence plays a crucial role in shaping marketing managers' intentions to use AI in sales and marketing, as it reflects the opinions, experiences, and actions of colleagues and industry peers, ultimately impacting the adoption of AI-driven tools (Venkatesh et al., 2003; Rogers, 2003; Fishbein & Ajzen, 1975; Kim & Kankanhalli, 2009; Wu & Chen, 2017; Huang & Rust, 2021; Bughin et al., 2017; Davenport & Ronanki, 2018; Kumar & Sharma, 2021).

5.2 Predictors affecting Actual Use of AI in Sales and Marketing

Behavioral Intention

The study finds that behavioral intention and peer influence are the only two predictor constructs with a significant direct impact on the actual use of AI in sales and marketing. The Theory of Planned Behavior (TPB) posits that behavioral intention is a significant predictor of actual behavior (Ajzen, 1991). According to this theory, an individual's intention to perform a certain behavior is directly influenced by their attitudes, subjective norms, and perceived behavioral control. In the context of AI adoption in sales and marketing, a strong behavioral intention to use AI-driven tools and technologies can lead to the actual use of these tools, as marketing managers are more likely to act on their intentions when they perceive the benefits and have the necessary resources and support (Venkatesh et al., 2003).

Empirical research supports the notion that behavioral intention is a strong predictor of actual technology adoption. For instance, a study by Wu and Chen (2017) found that behavioral intention significantly predicted the actual use of AI in marketing among professionals. Similarly, Venkatesh et al. (2003) demonstrated the importance of behavioral intention as a key determinant of technology adoption in their Unified Theory of Acceptance and Use of Technology (UTAUT) model.

According to the TPB, behavioral intention is influenced by three factors: attitude towards the behavior, subjective norms, and perceived behavioral control (Ajzen, 1991). In the context of AI adoption in sales and marketing, the attitude towards using AI-driven tools reflects marketing managers' positive or negative evaluations of the technology. Subjective norms represent the perceived social pressure to adopt AI, while perceived behavioral control refers to the marketing managers' belief in their ability to effectively use AI in their work. When marketing managers have a positive attitude, perceive supportive social norms, and believe they can effectively use AI, their behavioral intention to adopt AI in sales and marketing is strengthened, which in turn increases the likelihood of actual technology usage (Venkatesh et al., 2003; Wu & Chen, 2017).

Empirical studies have demonstrated the significant impact of behavioral intention on the use behavior of AI in sales and marketing. For example, Wu and Chen (2017) found a strong relationship between behavioral intention and the actual use of AI-driven marketing tools among professionals. Similarly, Kim and Kankanhalli (2009) reported that behavioral intention played a crucial role in determining the adoption of AI technologies.

The impact of behavioral intention on the use behavior of AI in sales and marketing can be further explained by the concept of self-efficacy. When marketing managers have a strong intention to adopt AI, they are more likely to develop the necessary skills and competencies to effectively use AI-driven tools (Compeau & Higgins, 1995). This increased self-efficacy can contribute to the successful implementation and usage of AI in sales and marketing, ultimately improving marketing performance and generating a competitive advantage for the organization (Kumar & Sharma, 2021).

The impact of behavioral intention on the use behavior of AI in sales and marketing can be understood through the lens of the TPB (Ajzen, 1991) and the UTAUT model (Venkatesh et al., 2003). Strong behavioral intention, driven by positive attitudes, supportive social norms, and perceived behavioral control, can lead to the successful adoption and use of AI in sales and marketing. Empirical research by Wu and Chen (2017) and Kim and Kankanhalli (2009), as well as the concept of self-efficacy (Compeau & Higgins, 1995), further supports the significant impact of behavioral intention on the use behavior of AI in sales and marketing.

Nevertheless, several barriers can hinder the development of a positive behavioral intention on the use of AI in sales and marketing. These barriers can be categorized into individual, organizational, and technological factors.

1. Individual factors play a crucial role in shaping marketing managers' behavioral intention towards adopting AI in sales and marketing. These factors can influence their attitudes, perceived social norms, and perceived behavioral control, which ultimately impact their intention to use AI-driven tools. Here, we elaborate on some key individual factors:

- Knowledge and skills: Marketing managers' level of knowledge and expertise in using AI-driven tools significantly impacts their behavioral intention to adopt the technology (Kelleher & Tierney, 2018). If they lack the necessary knowledge or skills, they may perceive AI as complex and challenging to use, leading to a negative attitude towards AI adoption (Venkatesh et al., 2003). To address this issue, organizations can invest in training programs and resources to help marketing managers develop the required AI-related skills and improve their understanding of the technology.
- Attitude towards AI: An individual's attitude towards AI in sales and marketing is influenced by their beliefs about the potential benefits and risks associated with the technology (Ajzen, 1991). If marketing managers perceive AI as a valuable tool that can enhance their performance, they are more likely to develop a positive attitude and stronger behavioral intention to adopt AI. Conversely, concerns about job loss, ethical issues, or loss of human touch in marketing activities may result in a negative attitude, reducing their intention to use AI (Kumar & Sharma, 2021).
- Self-efficacy: Self-efficacy refers to an individual's belief in their ability to

successfully perform a specific task or achieve a desired outcome (Bandura, 1977). In the context of AI adoption in sales and marketing, marketing managers with high self-efficacy are more likely to have a positive attitude and stronger behavioral intention to use AI-driven tools (Compeau & Higgins, 1995). Organizations can enhance self-efficacy by providing hands-on training, mentorship, and support to help marketing managers gain confidence in their ability to use AI effectively.

- Resistance to change: The natural human tendency to resist change can also impact marketing managers' behavioral intention to adopt AI in sales and marketing (Kim & Kankanhalli, 2009). Factors such as fear of job loss, status quo bias, or the discomfort associated with learning new processes and tools may lead to resistance to AI adoption. Organizations can manage this resistance by addressing employees' concerns, communicating the benefits of AI, and involving marketing managers in the AI implementation process to foster a sense of ownership and commitment.
- Personal innovativeness: Personal innovativeness refers to an individual's propensity to adopt and experiment with new technologies (Agarwal & Prasad, 1998). Marketing managers with high personal innovativeness are more likely to have a positive attitude and stronger behavioral intention to use AI in sales and marketing. To encourage innovativeness, organizations can foster a culture of continuous learning and experimentation, while recognizing and rewarding innovative behavior.

2. Organizational factors significantly influence marketing managers' behavioral intention to adopt AI in sales and marketing. These factors can shape the overall environment within which marketing managers operate, affecting their attitudes, perceived social norms, and perceived behavioral control related to AI adoption. Here, we elaborate on some key organizational factors:

- Organizational culture: An organization's culture, which encompasses shared values, beliefs, and practices, can play a pivotal role in determining marketing managers' behavioral intention to adopt AI (Bughin et al., 2017). A culture that supports innovation, risk-taking, and continuous learning encourages employees to adopt new technologies, such as AI, to improve their performance. Conversely, a risk-averse culture with limited support for innovation can impede the development of a positive behavioral intention towards AI adoption in sales and marketing. To foster a supportive culture, organizations can promote transparency, collaboration, and experimentation, while rewarding innovative thinking and risk-taking.
- Management support: The commitment and support of top management are crucial for the successful adoption of AI in sales and marketing (Kumar & Sharma, 2021). Marketing managers are more likely to develop a positive behavioral intention to use AI-driven tools if they perceive strong management support for AI initiatives. This support can be demonstrated through clear communication of AI adoption objectives, allocation of resources, and inclusion of AI-related goals in performance evaluations. Additionally, management can set an example by embracing AI-driven tools in their own work processes.
- Resource availability: The availability of resources, such as budget, time, and personnel, can impact marketing managers' behavioral intention to adopt AI in sales and marketing (Kumar & Sharma, 2021). Insufficient resources may hinder marketing managers from integrating AI-driven tools into their work processes, leading to a weak behavioral intention to use AI. Organizations can address this issue by allocating sufficient resources to AI initiatives and ensuring marketing managers have access to the necessary tools, training, and support to use AI

effectively.

- Organizational structure: A flexible and adaptable organizational structure can facilitate the adoption of AI in sales and marketing, as it allows for the necessary adjustments and changes required for AI integration (Bughin et al., 2017). A rigid, hierarchical structure, on the other hand, can create barriers to AI adoption by limiting communication, collaboration, and decision-making autonomy. To promote a more flexible structure, organizations can adopt a flatter hierarchy, empower employees to make decisions, and encourage cross-functional collaboration.
- Change management: The process of adopting AI in sales and marketing involves significant changes in workflows, processes, and roles, which can be challenging for marketing managers (Kumar & Sharma, 2021). Effective change management is essential for fostering a positive behavioral intention to adopt AI by addressing potential resistance, ensuring smooth transitions, and minimizing disruptions. Organizations can implement change management strategies, such as clear communication of the benefits and expectations of AI adoption, providing training and support, and involving marketing managers in the planning and implementation process to build commitment and ownership.

In summary, organizational factors, including culture, management support, resource availability, organizational structure, and change management, significantly impact marketing managers' behavioral intention to adopt AI in sales and marketing. Addressing these factors by fostering a supportive culture, providing sufficient resources, and implementing effective change management strategies can help organizations promote a positive behavioral intention and facilitate successful AI adoption.

3. Technological factors can significantly influence marketing managers' behavioral

intention to adopt AI in sales and marketing. These factors determine the perceived usefulness, ease of use, and compatibility of AI-driven tools, which can impact marketing managers' attitudes, perceived social norms, and perceived behavioral control related to AI adoption. Here, we elaborate on some key technological factors:

- Complexity and ease of use: The perceived complexity of AI-driven tools can negatively influence marketing managers' attitudes and behavioral intention to adopt them (Venkatesh et al., 2003). If AI tools are perceived as difficult to use or understand, marketing managers may be reluctant to integrate them into their work processes (Davis, 1989). To address this issue, AI solution providers should focus on developing user-friendly interfaces and tools that simplify the user experience. Additionally, organizations can invest in training and support resources to help marketing managers become proficient in using AI-driven tools.
- Integration and compatibility: The challenge of integrating AI-driven tools with existing systems and processes can act as a barrier to a positive behavioral intention to use AI in sales and marketing (Nguyen et al., 2020). If AI tools are not compatible with existing workflows and systems, marketing managers may be hesitant to adopt them. To overcome this barrier, organizations can work closely with AI solution providers to ensure seamless integration and compatibility with their existing systems. Additionally, organizations can consider adopting open standards and APIs to facilitate the integration of AI tools with various platforms and applications.
- Reliability and performance: Marketing managers' behavioral intention to adopt AI in sales and marketing can be influenced by the perceived reliability and

performance of AI-driven tools (Kumar & Sharma, 2021). If AI tools are perceived as unreliable or prone to errors, marketing managers may be less inclined to use them. To address this concern, AI solution providers should invest in rigorous testing, validation, and continuous improvement of their tools to ensure high levels of reliability and performance. Organizations can also establish monitoring mechanisms and feedback loops to identify and address performance issues promptly.

- Data quality and privacy: The effectiveness of AI-driven tools in sales and marketing is highly dependent on the quality and availability of data (Nguyen et al., 2020). Marketing managers may be hesitant to adopt AI if they perceive that their organization lacks the necessary data infrastructure or data quality to support AI initiatives. Furthermore, concerns about data privacy and security can also impact their behavioral intention to use AI-driven tools (Kumar & Sharma, 2021). To address these concerns, organizations should invest in robust data management practices, including data cleansing, standardization, and enrichment, and ensure compliance with data privacy and security regulations.
- Customization and adaptability: AI-driven tools that offer customization and adaptability features can have a positive impact on marketing managers' behavioral intention to adopt AI in sales and marketing (Kumar & Sharma, 2021). Customizable AI tools can be tailored to the specific needs, preferences, and requirements of marketing managers, making them more likely to perceive the tools as useful and effective. AI solution providers should focus on developing flexible and adaptable tools that can cater to various marketing use cases, industries, and organizational contexts.

Technological factors, including complexity, ease of use, integration, compatibility, reliability, performance, data quality, privacy, customization, and adaptability, significantly impact marketing managers' behavioral intention to adopt AI in sales and marketing. Addressing these factors by developing user-friendly, reliable, compatible, and customizable AI tools, and ensuring robust data management practices can help organizations promote a positive behavioral intention and facilitate successful AI adoption. In conclusion, various individual, organizational, and technological factors can act as barriers to developing a positive behavioral intention on the use of AI in sales and marketing. Overcoming these barriers requires addressing the knowledge and skill gaps, managing resistance to change, fostering a supportive organizational culture, allocating sufficient resources, simplifying AI tools, and ensuring their integration and compatibility with existing systems and processes (Kelleher & Tierney, 2018; Kumar & Sharma, 2021). To increase the adoption of AI in marketing and sales, organizations can focus on the following aspects:

- Training and education: Provide training and education programs to enhance employees' knowledge and skills related to AI-driven tools and technologies. This will help employees understand the benefits and potential applications of AI in their work processes.
- Management support: Ensure top management is committed to AI adoption and visibly supports its integration in sales and marketing activities. This can help create a positive environment for employees to embrace AI-driven tools.
- Allocate resources: Dedicate sufficient resources, such as budget, time, and personnel, to support AI initiatives. This will enable employees to access the necessary tools, training, and support to effectively use AI in their work.

- Foster a culture of innovation: Encourage a culture that values innovation, risk-taking, and continuous learning. This will help employees feel more comfortable with experimenting and adopting new technologies, such as AI.
- Effective change management: Implement change management strategies to address potential resistance, ensure smooth transitions, and minimize disruptions during AI adoption. This includes clear communication, training, and support, as well as involving employees in the planning and implementation process.
- Seamless integration: Collaborate with AI solution providers to ensure seamless integration and compatibility of AI-driven tools with existing systems and processes. This will minimize disruption and make it easier for employees to adopt AI in their daily work.
- Improve data quality and privacy: Invest in robust data management practices to ensure high-quality data and compliance with data privacy and security regulations. This will increase the effectiveness of AI-driven tools and alleviate employees' concerns related to data privacy.
- Customizable and adaptable tools: Collaborate with AI solution providers to develop and adopt AI tools that are flexible, customizable, and adaptable to the specific needs and preferences of the organization and its employees.
- Monitor and evaluate performance: Establish monitoring mechanisms and feedback loops to continuously evaluate the performance and effectiveness of AI-driven tools in sales and marketing. This will help identify areas for improvement and ensure AI tools deliver the desired results.
- Share success stories and best practices: Communicate success stories and best practices related to AI adoption within the organization to motivate and inspire

employees. This will also help them understand the practical applications and benefits of AI in their work processes.

The adoption of AI in sales and marketing offers numerous potential benefits, such as improved efficiency, customer insights, and personalization. The study assessing marketing managers' perception of using AI in sales and marketing found that performance expectancy, effort expectancy, and peer influence are important predictors affecting the behavioral intention to use AI. These constructs can be influenced by various individual, organizational, and technological factors.

Individual factors include personal experience, skills, and attitudes towards AI, which can be addressed through training and education programs. Organizational factors, such as culture, management support, resource availability, organizational structure, and change management, play a significant role in shaping the overall environment and employees' attitudes towards AI adoption. To promote a positive environment, organizations should foster a culture of innovation, allocate sufficient resources, and implement effective change management strategies.

Technological factors, including complexity, ease of use, integration, compatibility, reliability, performance, data quality, privacy, customization, and adaptability, can impact the perceived usefulness and ease of use of AI-driven tools. Addressing these factors by developing user-friendly, reliable, compatible, and customizable AI tools, and ensuring robust data management practices can help organizations promote a positive behavioral intention and facilitate successful AI adoption.

To increase the adoption of AI in marketing and sales, organizations should focus on providing training and education, ensuring management support, allocating resources, fostering a culture of innovation, implementing effective change management, integrating

AI seamlessly, improving data quality and privacy, developing customizable and adaptable tools, monitoring and evaluating performance, and sharing success stories and best practices. By addressing these aspects, organizations can overcome challenges and barriers, and successfully integrate AI in their sales and marketing processes.

Chapter 6: Conclusion

6.1 Summary

The study assessing marketing managers' perceptions of using AI in sales and marketing provides valuable insights into the factors influencing their behavioral intention to adopt AI-driven tools. The findings reveal that performance expectancy, effort expectancy, and peer influence are significant predictors of marketing managers' intention to use AI, which can, in turn, impact the actual adoption and use of AI in their work processes.

The study highlights the importance of addressing individual, organizational, and technological factors that can influence these predictor constructs. By focusing on training, education, management support, resource allocation, fostering a culture of innovation, and implementing effective change management strategies, organizations can create an environment conducive to AI adoption in sales and marketing.

Moreover, the development of user-friendly, reliable, compatible, and customizable AI tools, along with ensuring robust data management practices, can help organizations overcome technological barriers and improve the perceived usefulness and ease of use of AI-driven tools. This can contribute to positive behavioral intentions and facilitate successful AI adoption in sales and marketing.

The study also emphasizes the need for organizations to share success stories and best practices related to AI adoption, which can increase peer influence and motivate marketing managers to embrace AI-driven tools. This can lead to an increased actual use of AI in sales and marketing, unlocking the full potential of AI to drive growth, efficiency, and innovation in the field.

6.2 Implications

The results from the Importance-Performance Map Analysis (IPMA) help illuminate the impact of different exogenous constructs, or independent variables, on the endogenous construct, or the dependent variable, which is in this case the actual use of AI in marketing. According to the results, the most significant total effects on the actual use of AI in marketing are observed from behavioral intention, effort expectancy, and peer influence. This suggests that these factors play a critical role in determining whether AI is actually used in marketing operations.

1. Behavioral Intention: The relatively high total effect from behavioral intention suggests that marketing managers who show a strong intention to use AI are more likely to translate this intention into actual use. The stronger the intention to use AI, the higher the likelihood that AI will be utilized in marketing practices.
2. Effort Expectancy: This finding indicates that the perceived ease of using AI technologies significantly influences their actual use in marketing. If marketing managers perceive that AI tools are easy to learn and use, they are more likely to employ these tools in their work.
3. Peer Influence: This shows that the influence from peers plays a significant role in determining the use of AI in marketing. Marketing managers are likely to use AI if their peers are using it and share positive experiences or benefits from its use.

On the other hand, performance expectancy and facilitating condition have a smaller total effect on the actual use of AI in marketing. This suggests that the perceived usefulness of AI (performance expectancy) and the availability of supporting conditions (facilitating conditions) have a lesser impact on the actual implementation of AI in marketing compared to behavioral intention, effort expectancy, and peer influence.

1. Performance Expectancy: While performance expectancy is still a relevant factor, its lesser total effect suggests that the perceived improvement in job performance due to AI usage is less influential on actual AI use. This may indicate that the belief in AI's potential benefits alone is not enough to drive its actual use.
2. Facilitating Condition: Similarly, facilitating conditions have a lower total effect. This indicates that even when the necessary resources, infrastructure, and support are available, they may not necessarily lead to the use of AI unless the individuals have the intention and find it easy to use AI and are influenced by their peers to do so.

These findings highlight that while all five constructs of the UTAUT model are relevant, some constructs have a greater total effect on the actual use of AI in marketing. This understanding can help in prioritizing efforts towards fostering behavioral intention, lowering effort expectancy, and leveraging peer influence to enhance AI adoption in marketing.

6.3 Recommendations

Overall, the study provides a comprehensive understanding of the factors influencing marketing managers' intention to adopt AI in sales and marketing and offers practical recommendations for organizations seeking to harness the power of AI to transform their marketing and sales processes. By addressing the identified challenges and barriers, organizations can ensure the successful integration of AI, enabling them to stay competitive and achieve better results in an increasingly dynamic and data-driven marketplace.

Despite the valuable insights provided by the study, there are certain limitations that should be acknowledged. These limitations, along with suggested directions for future research, are as follows:

- Limited generalizability: The study is conducted within a specific geographical region which could limit the generalizability of the findings to other settings. Future research could explore the perceptions of marketing managers across different industries, regions, and organizational sizes to obtain a more comprehensive understanding of the factors influencing the behavioral intention to adopt AI in sales and marketing.
- Cross-sectional design: The study's cross-sectional design only provides a snapshot of marketing managers' perceptions at a specific point in time. As the adoption and use of AI in sales and marketing are dynamic processes, longitudinal research designs could be employed in future studies to assess changes in perceptions and behavioral intentions over time, as well as to identify causal relationships among the constructs.
- Qualitative insights: The study may have primarily employed quantitative methods to assess marketing managers' perceptions, which could limit the depth of understanding regarding the reasons behind their behavioral intentions. Future research could incorporate qualitative methods, such as interviews and focus groups, to obtain richer insights into the underlying motivations, beliefs, and experiences of marketing managers in relation to AI adoption.
- Additional factors: The study focused on performance expectancy, effort expectancy, and peer influence as the main predictors of marketing managers' behavioral intention to use AI in sales and marketing. However, there may be other factors, such as organizational readiness, trust in AI, and regulatory environment, which could also influence their intentions. Future research could explore the impact of these additional factors to develop a more comprehensive model of AI adoption

in sales and marketing.

- Implementation and outcomes: The study primarily focused on the factors influencing marketing managers' intentions to use AI but did not extensively investigate the actual implementation process and the outcomes of AI adoption in sales and marketing. Future research could examine the challenges faced during AI implementation, the factors that contribute to successful AI adoption, and the measurable outcomes of AI use in sales and marketing, such as improvements in efficiency, customer satisfaction, and revenue growth.

By addressing these limitations and exploring the suggested directions for future research, scholars can continue to build upon the current understanding of AI adoption in sales and marketing, ultimately providing more robust and actionable insights for organizations looking to harness the power of AI in their marketing and sales processes.

6.4 Conclusion

In conclusion, this study contributes significantly to the existing body of knowledge on AI adoption in marketing. It underscores the varying impact of different UTAUT constructs on the actual use of AI, thus providing a nuanced understanding that can inform more effective strategies for AI integration in marketing practices. As with any study, future research could build on these findings, investigating the causes of these impacts and the potential for their leverage in various organizational and industry contexts.

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Annexure: Questionnaire

Demographics

1. Industry

   a) Product Firm

   b) Service Firm

2. What is the size of your organization?

   a) Less than 100 employees

   b) More than 100 employees

3. Do your organization has very few decisions levels?

   a) Yes

   b) No

Please rate the Below Statements

(From 1 – strongly disagree to 7 – strongly agree)

Construct	Indicator	1	2	3	4	5	6	7
Performance Expectancy *(Venkatesh et al., 2003)*	PE01 - AI tools significantly improve sales and marketing efficiency							
	PE02 - AI can effectively analyze and interpret complex							

	data for sales and marketing							
	PEO3 - Using AI for sales and marketing will lead to better decision-making							
	PE04 - AI can help in identifying new sales and marketing opportunities e. AI contributes to increased sales and marketing effectiveness							
Effort Expectancy *(Venkatesh et al., 2003)*	EE01 - AI tools for sales and marketing are user-friendly							
	EE02 - Learning to use AI for sales and marketing is easy							
	EE03 - Implementing AI for sales and marketing tasks requires minimal effort							
	EE04 - The benefits of using AI for sales and marketing outweigh the effort required							
Facilitating Condition *(Venkatesh et*	FC01 - My organization provides the necessary resources to use AI for sales and marketing							

al., 2003)	FC02 - There is adequate support available to learn and use AI tools for sales and marketing							
	FC03 - Necessary infrastructure is in place to implement AI for sales and marketing							
Peer Influence *(Rana et al., 2016)*	PI01 - My peers in the industry regularly discuss the use of AI in sales and marketing.							
	PI02 - Colleagues in my network have adopted AI tools for sales and marketing.							
	PI03 - There is a strong peer consensus on the value of AI in sales and marketing.							
Behavioral Intention *(Dwivedi et al., 2019)*	BI01 - I intend to use AI tools for sales and marketing in the near future.							
	BI02 - I plan to increase my use of AI for sales and marketing tasks.							
	BI03 - I will actively seek opportunities to implement AI in							

	sales and marketing.							
Actual Use *(Venkatesh et al., 2003)*	AU01 - I frequently use AI tools for sales and marketing tasks							
	AU02 - AI is an essential component of my sales and marketing strategy							
	AU03 - I actively explore and implement new AI technologies for sales and marketing							

……………………………………………………………………………………….

THANK YOU