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# Predictive PLS-SEM Analysis of Artificial Intelligence Chatbots in Innovative Marketing

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**ABSTRACT**

Marketing has witnessed a digital transformation driven by the fast evolution of technology and international intelligence (AI), as businesses can now implement intelligent chatbot systems to boost customer interaction and improve the overall performance of the business. The study explores the relationships between Artificial Intelligence Chatbot Quality, customer trust, perceived ease of use, innovative marketing capability, customer experience, supply chain integration and business performance, applying predictive partial least squares structural equation modeling (PLS-SEM). A mediation analysis, PLSpredict, and importance–performance map analysis (IPMA) were used in SmartPLS 4 to analyse the primary data collected from 526 participants who have previously utilised AI-powered chatbots. The result show that AI Chatbot Quality significantly positively affects innovative marketing capability and customer experience, and customer trust and perceived ease of use positively influence customer experience. Customer experience positively influences supply chain integration and business performance and acts as a mediator between AI Chatbot quality and business performance. The study combines the TAM and RBV models into a single predictive model, offering theoretical perspectives and practical implications for organisations looking to enable their AI chatbots to enhance their innovative marketing efforts and gain a sustainable competitive edge.

**Keywords:** Artificial Intelligence, Chatbots, Innovative Marketing, Customer Experience, Predictive Partial Least Squares
**JEL Classifications:** C38, D83, L86, M31, O33

## 1. INTRODUCTION

In today's digital age, artificial intelligence (AI) is revolutionizing the way companies function, providing them with an array of tools that allows them to streamline operations, customize the customer experience, and make better business decisions. But, when it comes to AI powered technologies, chatbots have proven to be a useful digital tool for real-time communication, personalized recommendations, and improved customer service across various industries. Conversational AI is rapidly transforming customer service and paving the way for better customer relationships and operational efficiency (Davenport et al., 2020; Huang and Rust, 2021). With digital transformation picking up pace, AI Chatbots are now considered as an investment piece that can help them gain a better competitive advantage through innovative marketing projects, as mentioned in Kotler et al (2021), Verhoef et al (2021). AI-driven chatbots can achieve these goals by providing round-the-clock customer support, personalized product suggestions, and data analysis-driven engagement strategies that enhance customer satisfaction and loyalty (Kumar et al., 2019; Chatterjee et al., 2021). The insights derived from the customer interactions with the chatbots can help in fine-tuning marketing strategies and enhancing demand forecasting, inventory management, and customer responsiveness, thereby boosting the organization's supply chain integration and performance (Wamba et al., 2020; Mikalef et al., 2021). Although AI chatbots have emerged as a popular solution, the current research has been studies separately from technology, customer satisfaction or service quality. The interaction of these factors AI chatbot quality, customer trust, ease of use and innovative marketing capabilities on a unified predictive approach

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with respect to customer experience, supply chain integration, and business performance has received limited empirical attention. In addition, while there have been numerous studies that adopted partial least squares structural equation modeling (PLS-SEM) to analyze complex relationships between latent variables, only a few studies have used a predictive assessment employing PLSpredict to demonstrate the out-of-sample predictive performance of an AI-based marketing model (Hair et al., 2022; Sarstedt et al., 2019).

The focus of the research on prediction further demonstrates its appropriateness to technology and marketing research. Most prior research has taken the adoption of AI chatbots, customer trust, technology acceptance, and customers' satisfaction as individual research streams. At the same time, however, limited research has examined the impact of AI Chatbot quality on innovative marketing capability, customer experience, supply chain integration and business performance in a single framework of predictive PLS-SEM. The novelty of this study is to incorporate both TAM and RBV into a single predictive model that connects the AI Chatbot quality with the innovative marketing capability of the organizations, the customer experience, the supply chain integration and the business performance. It also plays a significant role by using Predictive PLS-SEM (PLSpredict), PLSpredict and IPMA to provide explanatory and predictive perspectives in marketing research for the benefit of innovative marketing research in the context of AI. Based on this, this study develops and empirically validates a predictive PLS-SEM model that explores the relationships between Artificial Intelligence Chatbot quality, customer trust, perceived ease of use, innovative marketing capability, customer experience, supply chain integration and business performance. The results advance marketing and management research by advancing the understanding of innovative marketing via AI and will provide practitioners with practical implications for organizations aiming to adopt chatbot technology for boosting customer value, data and input integration into their supply chain and business performance.

## 2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

### 2.1. Artificial Intelligence Chatbots

The advent of artificial intelligence (AI) has proved to be one of the most impactful technological advances in the way that businesses operate, how they engage customers, and the methods used in marketing. Conversational intelligence (CI), natural language processing (NLP) and machine learning (ML) are features of AI-powered chatbots, allowing companies to offer real-time, personalized customer interactions at scale. Unlike conventional customer service systems, AI chatbots learn and adapt over time based on customers' interactions and experiences, which helps to improve the quality of responses, efficiency of service, and the level of customer satisfaction (Dwivedi et al., 2021; Kaplan and Haenlein, 2020; West and Allen, 2018). With recent advances in conversational AI, companies are increasingly leveraging chatbots to offer 24/7 customer support, cut down on operational expenses, and gain insights from customer analytics, which helps to enhance their decision-making process (Zaki, 2019; Verhoef et al., 2021). AI chatbots have had a profound impact on the marketing and retail landscape. They are leveraging chatbots for customer service to respond to queries, make product recommendations, handle customer grievances, and guide customers toward purchase while gathering invaluable information from them to inform strategic decisions. (Davenport et al., 2020; Huang and Rust, 2021). Marketing scholars believe that AI is slowly changing the nature of customer interactions from transactions to intelligent and personalised interaction, which can help organisations create greater value and competitive advantage for its customers (Rust, 2020; Rust and Huang, 2021).

The advancement of AI chatbots is been expanded in the spaces of customer relationship management (CRM), sales support and omnichannel marketing. Conversational agents provide quicker responses, consistency of service, personalization, enabling better customer perception of service quality and trustworthiness (Ashfaq et al., 2020; Schuetzler et al., 2020). Likewise, the anthropomorphic features of chatbots have shown to enhance the involvement of customers by making the chats more human-like and positively impacting purchase intent (Blut et al., 2021). Research has also revealed that the success of the chatbot can rely on the system intelligence, understanding of context, accuracy of responses, and conversational skills (Belanche et al., 2020; Ben Mimoun et al., 2012). Multiple studies have highlighted how AI chatbots play a role within organizations in creating extensive customer interaction data, which aids in predictive analytics and business intelligence. These features help companies make more accurate predictions, segment their customers, and tailor their marketing efforts accordingly (Stone et al., 2020; Mariani et al., 2023). Service technologies with AI capabilities are becoming more and more a part of the front-end service interaction, enabling for automated, individualised and responsive service delivery. Wirtz et al. (2018) underlined the increase of intelligent service robots in frontline service encounters and they pointed out the possibility of changing the interaction between customers and technology, as well as the service experience. Therefore, the quality of AI chatbots has emerged as a vital organizational competitive and marketing asset that impacts customer experience and marketing outcomes. Therefore, the quality of AI chatbots has emerged as a vital organizational competitive and marketing asset that impacts customer experience and marketing outcomes.

### 2.2. Innovative Marketing Capability

In today's fast-changing digital business landscape, the changing nature of business practices has reshaped the conventional marketing approach into a technology-driven and customer-centric approach, which together has come to be known as 'innovative marketing'. Innovative marketing capability is the marketing's ability to harness new technologies, data analytics, and digital channels to create a tailored customer experience, build new promotional programs, and improve the value creation for customers (Kotler et al., 2021; Payne et al., 2017). By enabling real-time communication through various digital channels, customizable recommendations and constant engagement with customers, AI chatbots have emerged as one of the most essential tools for innovative marketing. In Marketing 5.0, the use of artificial intelligence, predictive analytics, automation, and the customer

data platform continues to represent the most advanced application in the field of marketing, with the goal of optimizing marketing results and making companies more competitive in the market (Kotler et al., 2021). Based on customer preferences, purchase history, and browsing trends, AI chatbots can provide tailored product suggestions and promotional offers (Kumar et al., 2019). This customer-oriented interaction not only makes the customer happier but also helps build long-term relationships and customer loyalty (Lemon and Verhoef, 2016). As AI becomes more prevalent in the marketing landscape, businesses have been investing in the use of chatbots to enhance customer relationship management (CRM), social media management, and e-commerce platforms. These integrations ensure more personalized communication and allow firms to gather more detailed data related to their customers, which can be valuable for strategic marketing actions (Yadav and Pavlou, 2014; Ismagilova et al., 2017). AI-driven marketing not only revolutionizes customer engagement by providing relevant information at the right moment in the customer journey but also boosts conversion rates and marketing efficiency (Grewal et al., 2017; Shankar, 2018).

According to Singh et al. (2019), artificial intelligence and digital technologies enable personalized and data-driven decision-making, thus enhancing customer engagement, marketing effectiveness and competitiveness of the organization. AI-powered innovative marketing nowadays does not only mean promotional communications for customers, but also the contribution to create value for customers, innovative digital services, and organizational competitiveness (Saura et al., 2022). Organizations with robust AI capabilities are better equipped to meet evolving customer expectations, deliver targeted marketing strategies, and make data-driven decisions to boost business performance (Mikalef et al., 2021). As a result, the quality of chatbots is expected to enhance innovativeness in marketing by creating intelligent interactions with customers to foster customer engagement and enhance the overall marketing efficiency. According to technology acceptance research, the valued features of AI chatbots in marketing efforts include intelligence, usefulness, reliability, and personalization that customers appreciate (Alalwan et al., 2017; Chatterjee et al., 2021). Businesses that can seamlessly incorporate AI chatbot capabilities into their marketing strategies are thus more likely to deliver exceptional customer experiences and provide competitive edge.

Based on the above discussion, the following hypotheses are proposed:

- $H_1$: Artificial Intelligence Chatbot Quality positively influences Innovative Marketing Capability.
- $H_2$: Artificial Intelligence Chatbot Quality positively influences Customer Experience.

## 2.3. Customer Trust in Artificial Intelligence Chatbots

It is well known that in digital environments, customers' trust is a key factor in shaping technology uptake and long-term relationships. Trust is a customer's belief that a technology is reliable, secure, competent and capable of performing its functions as expected (Gefen et al., 2003). Trust is a crucial precondition for customer acceptance, satisfaction, and usage in the context of AI chatbots as they are becoming more and more a substitute for human agents in customer service and marketing tasks (Saura et al., 2021; Siau and Wang, 2018). AI chatbots serve as a direct communication channel with customers, providing information about products, addressing customer service problems, completing transactions and even making tailored recommendations. If the customers think that the information generated by the chatbot is accurate, transparent and reliable, they will trust it (Ashfaq et al., 2020). In the same way, the customers' trust in AI technologies is high if the chatbot responds quickly, provides intelligent conversation and prompt information quality, which boosts their disposition to interact with digital services (Blut et al., 2021; Belanche et al., 2020). Trust is even more vital when AI chatbots gather information including personal information, purchase records, and behavioral data to tailor customer experiences. Saura et al. (2022) and Wirtz et al. (2023) found that privacy protection, ethical behavior of AI and transparency in data use have a significant effect on customers' level of trust in a chatbot. For this reason, companies with responsible governance of AI and securing digital environments will likely foster trust with their customers and sustain engagement with AI-powered marketing systems (Kaplan and Haenlein, 2020; Dwivedi et al., 2021). Studies have also shown that trusted AI Systems can enhance customer engagement, foster better customer relationships, and boost the effectiveness of digital marketing campaigns (Kumar et al., 2019). The trust of customers is thought to affect their perceived uncertainty around the purchasing process based on AI and positively impact customer experience on the digital service platforms (Ryu and Han, 2021). As a result, businesses that make trustworthy AI chatbot systems are likely to deliver better customer experiences and promote better marketing results.

Accordingly, the following hypothesis is proposed:

- $H_3$: Customer Trust positively influences Customer Experience.

## 2.4. Perceived Ease of Use

Perceived ease of use (PEOU) is one of the major constructs of the technology acceptance model (TAM) (Venkatesh et al., 2003; Venkatesh et al., 2012) which proposes that people will be more likely to use a technology if they believe that it is easy, understandable, and not very difficult to use. When it comes to intuitive, user-friendly, and efficient interactions that require minimal cognitive effort, the interface design of chatbots in AI Customer Service is crucial. AI chatbots streamline customer interactions by allowing for natural language interactions, immediate responses, and automatic support, even for parties lacking in technical expertise. When customer perception about a chatbot system is learning and use easy, they are eager to use the system again and increase customer satisfaction and technology acceptance (Chatterjee et al., 2021; Tamilmani et al., 2021). Likewise, customer satisfaction with providing service and their perceptions of service quality in online shopping and digital service interactions have been seen to improve when the chatbot interface is user-friendly (Yoo and Bai, 2019). Study on technology acceptance has been found repeatedly that the ease of use of the technology positively affects behavioral intention, adoption of technology and overall user experience (Tarhini et al., 2016; Alalwan et al., 2017). According to Alkhowaiter (2020), the factors that play the most

significant roles in driving digital banking and payment technology adoption include trust, perceived usefulness, ease of use and technological readiness. The unified theory of acceptance and use of technology (UTAUT) also theorizes that effort expectancy has a strong impact on a users' intention to use innovative digital technologies, in particular where technologies offer clear performance benefits (Venkatesh et al., 2012). Parasuraman and Colby (2015) has put together a technology readiness index (TRI 2.0) which shows that those with higher technology readiness are more ready to accept new digital technologies and AI-integrated services. Ease of use has repeatedly been shown as one of the most significant factors for AI adoption over the past year in marketing, CRM and ecommerce based applications (Saura et al., 2021). By implementing these measures, organizations can create AI chatbots that are more customer-friendly, enabling them to enhance the accessibility of their services, boost customer engagement, and pave the way for the successful execution of innovative marketing strategies. Convenient chatbot systems facilitate customers to engage more consistently, thus allowing companies to gather essential information on their customers that could be utilized for personalized marketing initiatives and business performance enhancement (Huang and Rust, 2018; Yadav and Pavlou, 2014). These interactions also help to shape customer satisfaction by minimizing search effort and enhance the efficiency of decision-making (Schuetzler et al., 2020). This paper builds on TAM and UTAUT and suggests that customers find AI chatbots easy to use are likely to be more satisfied, more engaged, and more accepted of AI-driven marketing services.

Therefore, the following hypotheses are proposed:

- $H_4$: Perceived ease of use positively influences customer experience.
- $H_5$: Perceived ease of use positively influences innovative marketing capability.

## 2.5. Customer Experience

In today's digital economy, customer experience has emerged as among the most critical factors in the organization's success. Defines the customers' mental, emotional and behavioral reactions to an organization based on their experience of the organization during the customer journey (Lemon and Verhoef, 2016). As AI-driven technologies are becoming more prevalent, customer journeys are being reimagined with an intelligent chatbot that meets the customer at many points of digital interaction, offering personalized, responsive and continuous service. An AI chatbot can help lower wait times, improve the quality of the communication, and speed up problem-solving, which will lead to an enhanced customer experience (Huang and Rust, 2018; Davenport et al., 2020). By using AI chatbots, businesses can deliver tailored product suggestions, targeted promotions, and immediate support based on customer behavior and desires. This type of personalized communication enhances customer engagement, satisfaction, and builds emotional connections between customers and brands (Kumar et al., 2019; Rust and Huang, 2021). Conversational AI enables ongoing and real-time customer interactions without time or location barriers, enhancing customer convenience and accessibility (Ashfaq et al., 2020). AI technologies have been shown to be effective in creating positive customer experiences, which has a positive impact on customer loyalty, repurchase intention, and positive WOM (Ryu and Han, 2021; Yadav and Pavlou, 2014). AI chatbots can also help companies better understand customer expectations and provide a more customized experience, while also helping them continually improve their services through its ability to analyse large amounts of data on interactions (Stone et al., 2020). Customer Experience (CX) has grown from a marketing metric to a strategic centre of competence within organisations, enabling them to innovate and maintain competitive advantage over time, as businesses move towards a customer-centric digital approach (Payne et al., 2017; Verhoef et al., 2021). Looking at the managerial standpoint, firms with stronger AI-driven customer experiences can more easily build a long-term relationship with customers, enhance customer retention and boost organizational performance (Mariani et al., 2023). Customer experiences that are positive result in valuable customer feedback that enables learning among the organization and help in continuous improvement among marketing and operational aspects (Wirtz et al., 2023). This suggests that customer experience will make it easier for organizations to communicate and coordinate across different business functions, thereby enhancing customer experience.

Therefore, the following hypothesis is proposed:

- $H_6$: Customer Experience positively influences Supply Chain Integration.

## 2.6. Supply Chain Integration

The process of supply chain integration involves strategic coordination and seamless interaction between the functions of the organization, its suppliers, its customers and the distribution partners leading to a smooth flow of information, synchronization of decision making processes and an enhanced performance of the supply chain (Wamba et al., 2020). In the digital era, AI-based tools have begun to greatly facilitate the integration of different organizations by providing real-time communication, predictive analytics, automated decision making, and better responsiveness to customers (Mikalef et al., 2021; Rai et al., 2019). By leveraging AI chatbots as intelligent communication tools that bridge the gap between customers and marketing, sales, inventory, logistics, and after-sales, AI can help drive supply chain integration. Chatbot interactions contribute hugely to an organization's current understanding of its customers' wants, buying patterns, product stock, and service desires. These learnings help businesses optimize their inventory management, demand forecasting, production planning and logistics coordination (Verhoef et al., 2021; Zaki, 2019). AI-driven interactions with customers also contribute to the visibility of the supply chain by enhancing information accuracy, minimizing uncertainty, and enabling collaborative decision-making with the supply chain partners (Wamba et al., 2020). In this regard, organizations that utilize and properly leverage AI generated customer intelligence in the supply chain processes can enhance responsiveness, lower operational costs, and provide better value to customers (Mikalef et al., 2021). The ability to integrate the supply chain with the help of AI helps companies adapt to changing market dynamics without compromising service quality and operational efficiency (Rai et al., 2019). According to the resource-based view (RBV), organizational resources like AI-powered supply chain integration

can be considered valuable organizational capabilities that have the potential to enhance organizational competitiveness and business performance. When marketing intelligence is incorporated into the processes of the organisation, it can support better resource utilization, inter-departmental coordination and organizational agility (Verhoef et al., 2021). Likewise, research concerning AI capability revealed that companies with high levels of technological resources generate more innovation, operational excellence, and competitive advantage in the long run (Dwivedi et al., 2021). In turn, customer experience created by AI chatbots will likely aid deeper integration of the organization, and integrated supply chain processes will likely bring benefits in the aspects of efficiency, responsiveness and customer satisfaction, leading to better organizational performance.

Therefore, the following hypotheses are proposed:

- $H_7$: Supply chain integration positively influences business performance.
- $H_8$: Customer experience positively influences business performance.

## 2.7. Business Performance

Business performance is the level at which an organization succeeds in meeting its strategic and operational goals by generating better financial results, customer satisfaction, market competitiveness, and organizational efficiency. Business performance assessment is currently done not only in terms of financial result, but also in terms of customer-centric indicators as well such as: customer retention, level of service, responsiveness to operations, innovation capacity and competitiveness in the long run (Rust, 2020). The use of artificial intelligence (AI) in marketing and business processes has greatly changed the value creation process, processes optimization and organizational performance improvement (Davenport et al., 2020). Customer engagement forms a crucial part of business operations, and AI-powered chatbots play a valuable role in enhancing it, as they boost customer satisfaction, streamline operations, maintain consistency, and deliver highly personalized customer experiences. These intelligent systems can be used for organizations to enhance customer acquisition and retention, and help them obtain valuable insights from their customers that can be used for strategic decision making (Huang and Rust, 2021). AI-generated customer data can also aid predictive analytics, enabling organizations to tweak marketing strategies, estimate customer demands, and enhance source allocation (Stone et al., 2020). This opens the door for companies using AI-powered marketing technologies to increase the productivity of their organizations and keep a competitive edge (Kaplan and Haenlein, 2020). Recent studies show that the capacity of AI improves the agility of the organizations by helping companies become faster with new demands of their customers and market changes (Mikalef et al., 2021). Customer relationship management (CRM) empowered by AI can also bolster customer loyalty and business profitability by delivering personalized engagement and ongoing customer interactions (Saura et al., 2021). Similarly, innovative marketing leveraging conversational AI could have a positive impact on customer acquisition, customer lifetime value, and organization competitiveness (Kumar et al., 2019). With the advent of AI, big data analytics, and the digital transformation, AI chatbots have thus emerged as valuable tools for organizations, enhancing marketing efforts and overall business performance (Verhoef et al., 2021; Mariani et al., 2023).

## 2.8. Theoretical Foundation

The proposed research framework is mostly drawn from the model of technology acceptance (TAM) as well as resource based view (RBV). Theory of planned behavior (TPB) by Ajzen (1991) has proven that the main factors that determine technology adoption behaviour are attitude, subjective norm, and perceived behavioural control. As per TAM, accepting new technologies depends upon the perception that they are useful and easy to use (Venkatesh et al., 2003; Venkatesh et al., 2012). In the realm of AI chatbots, customer trust and perceived ease of use have an impact on customer acceptance, satisfaction, and engagement with AI-powered marketing platforms. These behavioural reactions then improve customers' experience and enable the implementation of innovative marketing initiatives to be successful (Gefen et al., 2003; Tamilmani et al., 2021). Along with TAM, the resource based view posits that organizations gain sustainable competitive advantage through the development of organizational resources that are valuable, rare, inimitable and non-substitutable (Rai et al., 2019). AI chatbot capability combined with innovative marketing capability and supply chain integration is strategic organizational resources that contribute to the value creation for customers, operational efficiency and organizational competitiveness (Payne et al., 2017; Wamba et al., 2020). Combining TAM and RBV, thus, yields a holistic theoretical basis for understanding the link between AI capabilities and organization performance. Prediction-oriented research has also been strongly advocated in recent methodological literature; however, PLS-SEM has been one of the most fashionable methods used to address complex causal relationships in management and marketing research literature. With the help of PLSpredict, researchers can analyze the out-of-sample predictive ability of structural models, thereby extending the applicability of empirical research (Hair et al., 2017; Hair et al., 2022; Henseler et al., 2015; Henseler et al., 2016; Jöreskog and Wold, 1982; Ringle et al., 2020; Ringle et al., 2024; Sarstedt et al., 2019).

Therefore, the following hypothesis is proposed:

- $H_9$: Customer Experience mediates the relationship between Artificial Intelligence Chatbot Quality and Business Performance.

## 2.9. Conceptual Model

The theoretical arguments presented above suggest that customer experience will be one of the key avenues that enable the use of AI to enhance organizational performance. Customer experiences have a positive impact on the responsiveness of the organization, repeat purchase, and customer loyalty, all of which affect business outcomes (Lemon and Verhoef, 2016; Rust and Huang, 2021). Conceptual model summary the measurement items were adapted from existing studies based on the proposed theoretical framework, and the nine research hypotheses, to operationalize the nine latent constructs. To guarantee content valid and construct reliability, the questionnaire was structured on the basis of the scales already validated. The constructs, measurement items and the associated source references are given in Table 1.

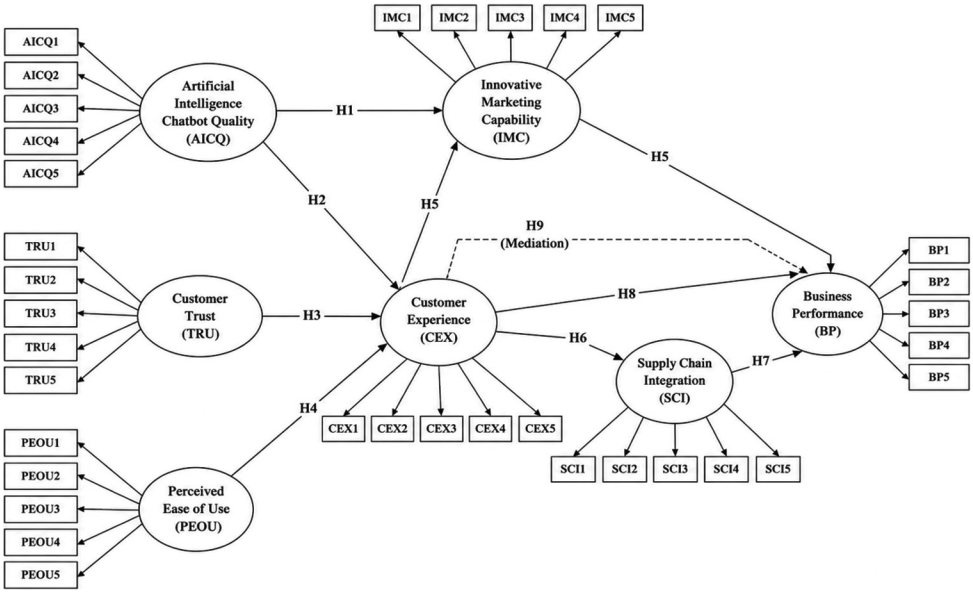
The proposed conceptual framework is based on the operationalization of constructs of the study. Based on the theoretical arguments presented and the measurement structure, Figure 1 shows the hypothesized relationships among the seven latent constructs in this study.

The conceptual framework is an overview of the theoretical relationships hypothesized in this study and is used to guide empirical testing. Research Methodology section describes the research methodology used to validate the proposed research model and to discuss the hypothesized relationship. Based on

**Table 1: Constructs and measurement items**

| Construct | Code | Measurement item | Adapted from |
|---|---|---|---|
| Artificial intelligence chatbot quality (AICQ) | AICQ1 | The AI chatbot provides accurate responses to my queries. | Ashfaq et al. (2020); Huang and Rust (2021) |
| | AICQ2 | The AI chatbot understands my requirements effectively. | Ashfaq et al. (2020) |
| | AICQ3 | The AI chatbot provides personalized recommendations based on my preferences. | Davenport et al. (2020); Kumar et al. (2019) |
| | AICQ4 | The AI chatbot responds quickly to my requests. | Chatterjee et al. (2021) |
| | AICQ5 | Overall, the AI chatbot performs efficiently during customer interactions. | Blut et al. (2021) |
| Customer trust (CT) | CT1 | I trust the information provided by AI chatbots. | Gefen et al. (2003) |
| | CT2 | AI chatbots adequately protect my personal information. | Siau and Wang (2018) |
| | CT3 | AI chatbots are reliable when making purchase-related decisions. | Ashfaq et al. (2020) |
| | CT4 | I feel secure while interacting with AI chatbots. | Saura et al. (2021) |
| Perceived ease of use (PEOU) | PEOU1 | Learning to use AI chatbots is easy for me. | Venkatesh et al. (2003) |
| | PEOU2 | Interacting with AI chatbots requires little effort. | Venkatesh et al. (2012) |
| | PEOU3 | AI chatbots are user-friendly and easy to navigate. | Chatterjee et al. (2021) |
| | PEOU4 | Using AI chatbots is clear and understandable. | Tamilmani et al. (2021) |
| Innovative marketing capability (IMC) | IMC1 | AI chatbots enable personalized marketing campaigns. | Kotler et al. (2021) |
| | IMC2 | AI chatbots improve communication with customers. | Davenport et al. (2020) |
| | IMC3 | AI chatbots enhance the effectiveness of promotional activities. | Kumar et al. (2019) |
| | IMC4 | AI chatbots support innovative digital marketing strategies. | Huang and Rust (2021) |
| Customer experience (CX) | CX1 | Using AI chatbots provides an enjoyable experience. | Lemon and Verhoef (2016) |
| | CX2 | AI chatbots improve my overall shopping experience. | Huang and Rust (2018) |
| | CX3 | AI chatbots make purchasing products and services more convenient. | Verhoef et al. (2021) |
| | CX4 | Overall, I am satisfied with my interactions with AI chatbots. | Ryu and Han (2021) |
| Supply chain integration (SCI) | SCI1 | AI chatbots improve communication across supply chain functions. | Wamba et al. (2020) |
| | SCI2 | AI chatbots facilitate real-time information sharing among departments. | Mikalef et al. (2021) |
| | SCI3 | AI chatbots improve coordination between marketing and supply chain operations. | Verhoef et al. (2021) |
| | SCI4 | AI chatbots enhance order processing and service responsiveness. | Wamba et al. (2020) |
| Business performance (BP) | BP1 | AI chatbots improve customer satisfaction. | Kumar et al. (2019) |
| | BP2 | AI chatbots contribute to higher sales performance. | Davenport et al. (2020) |
| | BP3 | AI chatbots strengthen customer retention and loyalty. | Rust (2020) |
| | BP4 | AI chatbots improve the overall performance of the organization. | Huang and Rust (2021) |

**Figure 1:** Conceptual framework



the technology acceptance model and the resource based view, this study introduces an integrated predictive model of seven constructs: Artificial Intelligence Chatbot quality, customer trust, perceived ease of use, innovative marketing capability, customer experience, supply chain integration, and business performance. The model assumes that the quality of AI chatbot directly boosts innovative marketing and customer experience, whereas customer trust and perceived ease of use are shown to have a direct impact on customer experience and innovative marketing. Customer experience helps supply chain integration and enhances business performance while integration in the supply chain contributes to Organizational performance. Lastly, customer experience is hypothesized to serve as a mediator between the quality of the AI chatbot and business performance. Current literature is extended by merging the concepts of AI-driven marketing strategies, customer behaviour and supply chain management into a single predictive PLS-SEM model, explaining causal relationships and predictive performance in today's digital business environments.

## 3. RESEARCH METHODOLOGY

### 3.1. Research Design

The research design used in this study was quantitative, cross sectional, and explanatory because it was conducted to explain the relationships between each of the variables, which were artificial intelligence (AI) Chatbot Quality, Customer Trust, PEU, Innovative Marketing Capability, Customer Experience, Supply Chain Integration, and Business Performance. Quantitative research was appropriate as the study aimed to empirically test the proposed conceptual model and test causal relationships between multiple latent constructs with the use of Structural Equation Modeling (Hair et al., 2017; Hair et al., 2022). The study model was developed with two perspectives: behavioural and strategic perspectives, in respect to AI-enabled innovative marketing, using the technology acceptance model (TAM) and the resource based view (RBV) respectively.

### 3.2. Population, Sampling, and Data Collection

The target population consisted of the consumers who have already had an experience with AI-powered chatbots for online shopping, customer support, banking, travel, retail, healthcare, food delivery or other digital services platforms. The respondents were selected through the purposive sampling approach because they were assumed to have a prior knowledge of interacting with AI chatbots, enabling them to contribute meaningful answers on the study constructs. Primary data were gathered using a structured online questionnaire sent out through Google Forms via email and social media. The questionnaire was pre-test reviewed by three scholars who have a background of marketing, artificial intelligence (AI) and supply chain management (SCM) (content validity and clarity). The items in the questionnaire were tested on a pilot study consisting of 35 respondents and were found to be understandable and had satisfactory internal consistency. Fifty-four-hundred and eight questionnaires were received. Following the removal of questionnaires with incomplete responses, and those with straight-lining or missing values, 526 questionnaires were used in statistical analysis with an effective response rate of 95.99%. The sample size was larger than the minimum requirement for PLS-SEM and also had sufficient statistical power to test the proposed SRL model (Hair et al., 2022; Henseler et al., 2016). A descriptive analysis of the respondents was first conducted to gain insights into the nature of the sample and to ensure the respondents were a representative sample of users of AI chatbot technologies. Table 2 shows the profile of the respondents.

The demographic profile showcases that the respondents have a wide range of age, education, profession, and knowledge of the use of AI chatbots, thus establishing a proper representative sample for the study of the proposed research model. In the next section, the measurement instrument that was employed to capture the constructs of the study is described.

### 3.3. Measurement Instrument

There were two parts to the questionnaire. The first section gathered the demographic data of the respondents such as gender, age, educational qualification, occupation, and how often they used AI chatbots. The seven latent constructs were assessed using the previously validated measurement scales that were adapted from existing studies in the

**Table 2: Respondent demographics**

| Demographic variable | Category | Frequency (n) | Percentage |
|---|---|---|---|
| Gender | Male | 301 | 57.2 |
| | Female | 218 | 41.4 |
| | Prefer not to say | 7 | 1.4 |
| | Total | 526 | 100 |
| Age (Years) | 18-25 | 148 | 28.1 |
| | 26-35 | 189 | 35.9 |
| | 36-45 | 121 | 23 |
| | 46-55 | 50 | 9.5 |
| | Above 55 | 18 | 3.4 |
| | Total | 526 | 100 |
| Educational qualification | Higher Secondary | 39 | 7.4 |
| | Diploma | 34 | 6.5 |
| | Bachelor's Degree | 241 | 45.8 |
| | Master's Degree | 179 | 34 |
| | Doctorate | 33 | 6.3 |
| | Total | 526 | 100 |
| Occupation | Student | 102 | 19.4 |
| | Private sector employee | 224 | 42.6 |
| | Government employee | 56 | 10.6 |
| | Business/ self-employed | 96 | 18.3 |
| | Others | 48 | 9.1 |
| | Total | 526 | 100 |
| Frequency of AI Chatbot Usage | Daily | 146 | 27.8 |
| | Weekly | 195 | 37.1 |
| | Monthly | 117 | 22.2 |
| | Occasionally | 68 | 12.9 |
| | Total | 526 | 100 |
| Primary purpose of AI Chatbot usage | Online Shopping | 152 | 28.9 |
| | Customer Support | 133 | 25.3 |
| | Banking and Financial Services | 67 | 12.7 |
| | Travel and Hospitality | 54 | 10.3 |
| | Food Delivery | 49 | 9.3 |
| | Healthcare | 28 | 5.3 |
| | Education | 24 | 4.6 |
| | Others | 19 | 3.6 |
| | Total | 526 | 100 |

second section. The constructs comprised the components artificial intelligence Chatbot quality (five items), customer trust (four items), perceived ease of use (four items), Innovative marketing capability (four items), customer experience (four items), supply chain integration (four items), and business performance (four items). AI-driven innovative marketing-focused minor wording changes were implemented, while retaining the original meaning of each item. All the measurement items were evaluated on a 5-point likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree that is commonly used for behavioural and marketing research on latent constructs (Venkatesh et al., 2012; Hair et al., 2022).

### 3.4. Data Analysis Technique

The data collected in this study were analysed using SmartPLS 4 software, which is suitable for complex research models involving multiple constructs, mediation effects and analysis that is oriented toward predicting research results (Ringle et al., 2024). partial least squares structural equation modeling (PLS-SEM) was chosen due to being able to handle non-normal data distributions, strong parameter estimation capabilities for predictive research, and the fact that it prioritizes variance explanation in models (Hair et al., 2022; Ringle et al., 2020).

According to Byrne (2016), SEM is a very rigorous method to assess the reliability of measures, construct validity and causal relationships between the latent variables in the behavior research literature. The analysis was carried out in a two-stage approach which is recommended in the PLS-SEM literature. The measurement model was assessed first by means of indicator loadings, Cronbach's alpha, composite reliability (CR), average variance extracted (AVE), and the Heterotrait-Monotrait ratio (HTMT) (Henseler et al., 2015; Sarstedt et al., 2019). The assessment of the structural model was then evaluated based on the path-coefficients (β), coefficient of determination ($R^2$), predictive relevance ($Q^2$), effect size ($f^2$) and bootstrapping analysis results obtained from 5000 resamples, which aim to test the significance of the hypotheses proposed (Hair et al., 2022). In order to test the predictive accuracy of the model, the predictions generated by PLSpredict were compared with that of a linear benchmark model by computing root mean squared error (RMSE) and mean absolute error (MAE) between the two models. This prediction-oriented evaluation goes beyond the traditional explanatory evaluation and highlights the model's practicality in the context of innovation marketing research using AI (Shmueli et al., 2019; Hair et al., 2022).

## 4. RESULT ANALYSIS

First, the empirical analysis started with the evaluation of the measurement model to establish reliability and validity of the latent constructs and then the study proceeded with the investigation of structural relationships. The reliability and convergent validity were performed using Factor loading, Cronbach alpha, composite reliability (CR) and average variance extracted (AVE).

The adequacy of the measurement model is confirmed as shown in Tables 3a and b. The factor loadings were above 0.70,

**Table 3a: Measurement model assessment: reliability, convergent validity, and outer collinearity diagnostics**

| Construct | Item | Factor loading | Cronbach's alpha | Composite reliability (CR) | Average variance extracted (AVE) | Outer VIF |
|---|---|---|---|---|---|---|
| Artificial intelligence Chatbot quality (AICQ) | AICQ1 | 0.862 | 0.911 | 0.934 | 0.739 | 2.184 |
| | AICQ2 | 0.874 | | | | 2.436 |
| | AICQ3 | 0.847 | | | | 2.512 |
| | AICQ4 | 0.856 | | | | 2.361 |
| | AICQ5 | 0.858 | | | | 2.294 |
| Customer trust (CT) | CT1 | 0.881 | 0.892 | 0.925 | 0.755 | 2.148 |
| | CT2 | 0.859 | | | | 2.307 |
| | CT3 | 0.869 | | | | 2.456 |
| | CT4 | 0.867 | | | | 2.274 |
| Perceived ease of use (PEOU) | PEOU1 | 0.853 | 0.887 | 0.922 | 0.748 | 2.203 |
| | PEOU2 | 0.871 | | | | 2.481 |
| | PEOU3 | 0.862 | | | | 2.335 |
| | PEOU4 | 0.867 | | | | 2.289 |
| Innovative marketing capability (IMC) | IMC1 | 0.866 | 0.904 | 0.933 | 0.776 | 2.671 |
| | IMC2 | 0.885 | | | | 2.824 |
| | IMC3 | 0.881 | | | | 2.786 |
| | IMC4 | 0.877 | | | | 2.694 |
| Customer experience (CX) | CX1 | 0.871 | 0.896 | 0.928 | 0.763 | 2.593 |
| | CX2 | 0.878 | | | | 2.726 |
| | CX3 | 0.869 | | | | 2.648 |
| | CX4 | 0.872 | | | | 2.705 |
| Supply chain integration (SCI) | SCI1 | 0.864 | 0.893 | 0.926 | 0.758 | 2.401 |
| | SCI2 | 0.872 | | | | 2.528 |
| | SCI3 | 0.868 | | | | 2.614 |
| | SCI4 | 0.876 | | | | 2.487 |
| Business performance (BP) | BP1 | 0.873 | 0.901 | 0.931 | 0.771 | 2.557 |
| | BP2 | 0.884 | | | | 2.689 |
| | BP3 | 0.875 | | | | 2.602 |
| | BP4 | 0.878 | | | | 2.544 |

Cronbach's alpha, Composite Reliability and AVE were within the recommended range, indicating the high reliability and convergent validity. The outer VIFs for all constructs were below 3.3, as were the inner VIFs, suggesting that there was no concern about multicollinearity and that the constructs were appropriate for further analysis of the structural model. All constructs show acceptable internal consistency and convergent validity. After reliability assessment, the analysis of discriminant validity has been performed then using Fornell-Larcker criterion and Heterotrait-Monotrait (HTMT) ratio.

The Fornell–Larcker criterion in table 4a indicates that the square roots of the AVEs for each construct are higher than the construct inter-correlations, hence reinforcing discriminant validity. The HTMT ratio was then evaluated to provide further evidence of discriminant validity.

The adequacy of the measurement model and structural models are confirmed by Tables 4b and 4c. The recommended threshold value was 0.90 and all the HTMT were lower than this indicating discriminant validity. In addition, the model fit indexes (SRMR, d_ULS, d_G, and NFI) met the recommended criteria, suggesting that the proposed PLS-SEM model has a good fit with the observed data. After ensuring the measurement model met all the validity and reliability standards, the proposed structural model was tested using SmartPLS 4. The results of the estimated structural model are depicted in Figure 2, which shows the relationships among the latent constructs.

The SmartPLS structural model is presented in Figure 2, which shows the measurement model factor loadings, standardized path coefficients and R2 values that provide support for the proposed relationships between the seven latent constructs in an empirical sense. The significance of the proposed relationships, effect sizes, the explanatory power and the predictive relevance of the structural model were then examined. The detailed structural model assessment is shown in Tables 5a-c.

**Table 3b: Inner variance inflation factor (inner VIF) assessment**

| Endogenous construct | Predictor construct | Inner VIF |
|---|---|---|
| Innovative marketing capability | Artificial intelligence chatbot quality | 1.846 |
| | Perceived ease of use | 1.846 |
| Customer experience | Artificial intelligence chatbot quality | 2.318 |
| | Customer trust | 2.041 |
| | Perceived ease of use | 2.226 |
| Supply chain integration | Customer experience | 1 |
| Business performance | Customer experience | 2.147 |
| | Supply chain integration | 2.147 |

After the statistical significance of the structural path coefficients and effect sizes were determined, the explanatory power of the endogenous constructs was tested by using the coefficient of determination ($R^2$).

Stone–Geisser's $Q^2$ statistic was used to evaluate the predictive relevance of the endogenous constructs in addition to the explanatory power.

With satisfactory structural model quality, the study also explored the mediation effect of Customer Experience in the relationship between the AI Chatbot quality and the business performance.

Mediating effect of customer experience between artificial intelligence Chatbot quality and business performance is shown in the Figure 3 where there are significant direct, indirect (mediation) and total effects supporting the proposed mediation hypothesis ($H_9$). The mediation model is a visual model that shows how the direct, indirect and total effects occur between the relevant constructs. The mediation analysis was conducted to understand that the effect of Artificial Intelligence Chatbot quality on business performance is mediated through customer experience, hence, customer interaction is the key way to derive the benefits of the implementation of an artificial intelligence Chatbot. Investing in a quality chatbot system enhances customer satisfaction, engagement, and service experiences, thus bolstering the corporate's overall performance. Based on this finding, Customer Experience is emerging as a key enabler between technological capability and business outcomes, and believes that organizations must aim to provide personal, reliable and user-friendly Customer Experience with their AI chatbot implementation to enable the best value of their AI investments. Table 6 summarizes the statistical significance of all the proposed hypotheses.

The structural model validates the explanation power of the proposed model, however, the most recent guidelines for PLS-SEM suggest the examination of the prediction performance with PLSpredict. For this reason, the predictive validity of the model was assessed and is shown in Table 7.

In addition to prediction accuracy, managerial implications can be drawn from constructs, both in terms of their importance and their performance, through an importance–performance map analysis (IPMA).

**Table 4a: Fornell–Larcker criterion**

| Constructs | AICQ | CT | PEOU | IMC | CX | SCI | BP |
|---|---|---|---|---|---|---|---|
| Artificial intelligence chatbot quality (AICQ) | **0.86** | | | | | | |
| Customer trust (CT) | 0.621 | **0.87** | | | | | |
| Perceived ease of use (PEOU) | 0.648 | 0.59 | **0.865** | | | | |
| Innovative marketing capability (IMC) | 0.714 | 0.61 | 0.673 | **0.88** | | | |
| Customer experience (CX) | 0.701 | 0.69 | 0.696 | 0.74 | **0.87** | | |
| Supply chain integration (SCI) | 0.644 | 0.6 | 0.615 | 0.71 | 0.74 | **0.87** | |
| Business performance (BP) | 0.626 | 0.59 | 0.604 | 0.69 | 0.76 | 0.78 | **0.88** |

Figure 4 shows the importance–performance map analysis (IPMA) illustrating that the constructs with the highest importance to enhance Business Performance with strategic AI-based marketing are customer experience, artificial intelligence Chatbot quality, and supply chain integration. The numerical values, rank and managerial priorities are summarized in Tables 8a-c.

The constructs were ranked based on their importance and performance scores with respect to the contribution they make to Business Performance.

The ranking outcomes were then converted into managerial priorities in order to help guide organisations in prioritising their resources based on the most impactful capabilities they enable through AI.

It can be seen that the predictive accuracy of the proposed PLS-SEM model is better than the linear benchmark model as the prediction errors of the two models is compared visually in Figure 5. Artificial Intelligence chatbot quality and supply chain integration were among the most important customer experience-related factors that led to business performance in the importance performance map analysis (IPMA). The findings indicate that there is a need for companies to focus more on improving customer interactions with intelligent, personalized and responsive AI chatbot systems and making it more integrated in their operation. Customer Trust and Perceived Ease of Use were comparatively less important, but enhancing these aspects can aid in further facilitating technology adoption and customer satisfaction. The IPMA overall results clearly indicate managerial priorities to ensure the optimal performance of their marketing activities using AI.

Figure 5 shows the difference in prediction errors between the PLS Model and the linear model. The predictive performance of the

**Table 4b: Heterotrait–Monotrait (HTMT) ratio**

| Constructs | AICQ | CT | PEOU | IMC | CX | SCI | BP |
|---|---|---|---|---|---|---|---|
| AICQ | — | | | | | | |
| CT | 0.714 | — | | | | | |
| PEOU | 0.748 | 0.68 | — | | | | |
| IMC | 0.812 | 0.7 | 0.764 | — | | | |
| CX | 0.793 | 0.78 | 0.786 | 0.84 | — | | |
| SCI | 0.726 | 0.69 | 0.704 | 0.8 | 0.84 | — | |
| BP | 0.703 | 0.68 | 0.691 | 0.77 | 0.86 | 0.88 | — |

**Table 4c: Model fit assessment**

| Model fit index | Saturated model | Estimated model | Recommended threshold | Result |
|---|---|---|---|---|
| Standardized Root Mean Square Residual (SRMR) | 0.054 | 0.058 | <0.08 | Good Fit |
| Squared Euclidean Distance (d_ULS) | 1.186 | 1.248 | HI95>Observed Value* | Acceptable |
| Geodesic Distance (d_G) | 0.764 | 0.801 | HI95>Observed Value* | Acceptable |
| Normed Fit Index (NFI) | 0.931 | 0.924 | >0.90 | Good Fit |

**Table 5a: Structural model assessment result**

| Structural path | Path coefficient (β) | Standard deviation | t-value | P-value | Effect size ($f^2$) | Decision |
|---|---|---|---|---|---|---|
| AICQ→IMC (H1) | 0.531 | 0.041 | 12.951 | <0.001 | 0.393 | Supported |
| AICQ→CX (H2) | 0.296 | 0.048 | 6.167 | <0.001 | 0.126 | Supported |
| CT→CX (H3) | 0.247 | 0.044 | 5.614 | <0.001 | 0.091 | Supported |
| PEOU→CX (H4) | 0.281 | 0.047 | 5.979 | <0.001 | 0.114 | Supported |
| PEOU→IMC (H5) | 0.338 | 0.042 | 8.048 | <0.001 | 0.187 | Supported |
| CX→SCI (H6) | 0.736 | 0.029 | 25.379 | <0.001 | 1.181 | Supported |
| SCI→BP (H7) | 0.462 | 0.04 | 11.55 | <0.001 | 0.307 | Supported |
| CX→BP (H8) | 0.381 | 0.039 | 9.769 | <0.001 | 0.218 | Supported |

**Figure 2:** SmartPLS structural model

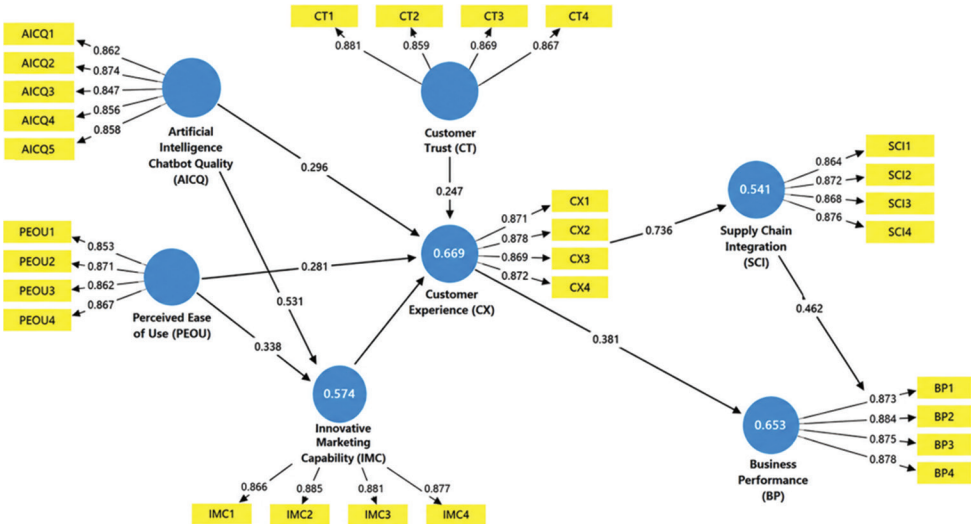


**Figure 3:** Mediation analysis model: Direct, indirect, and total effects of customer experience

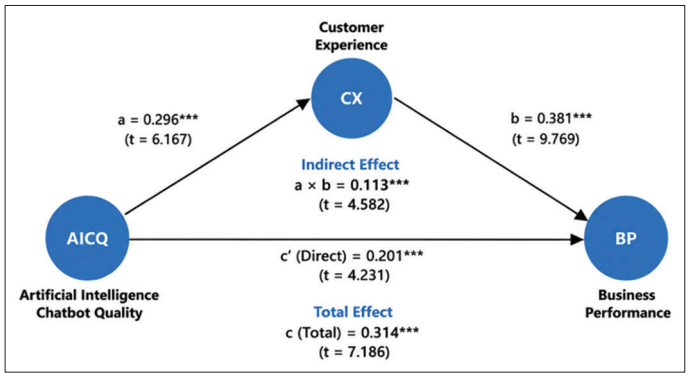



**Table 5b: Structural model assessment $R^2$, adjusted $R^2$**

| Endogenous construct | $R^2$ | Adjusted $R^2$ | Interpretation |
|---|---|---|---|
| Innovative marketing capability | 0.574 | 0.572 | Moderate |
| Customer experience | 0.669 | 0.667 | Substantial |
| Supply chain integration | 0.541 | 0.54 | Moderate |
| Business performance | 0.653 | 0.651 | Substantial |

**Table 5c: Structural model assessment $Q^2$**

| Endogenous construct | $Q^2$ | Interpretation |
|---|---|---|
| Innovative marketing capability | 0.414 | Large predictive relevance |
| Customer experience | 0.482 | Large predictive relevance |
| Supply chain integration | 0.367 | Large predictive relevance |
| Business performance | 0.445 | Large predictive relevance |

PLS model and the linear model (LM) were compared in terms of RMSE values. These small prediction errors seen in the PLS model points to its better out-of-sample predictive performance in all endogenous constructs. The prediction errors of PLS model showed that the proposed model has high predictive power out of sample, as the PLS model showed lower prediction errors than the benchmark linear model in all endogenous constructs. The results show that the framework provides an effective tool for understanding the links between AI chatbot quality, customer experience, and business performance and can be used to accurately forecast future results. The model has practical value for managers who are interested in predicting organizational performance and also can be useful to the increasing focus on predictive analytics in modern PLS-SEM research. The measurement and structural model, mediation analysis, predictive assessment, and the results of the IPMA have supported the proposed research framework thoroughly.

## 5. DISCUSSION

The current research analyzed the effect of artificial intelligence (AI) Chatbot quality, customer trust and perceived ease of use on innovative marketing capability, customer experience, supply chain integration and business performance with the application of predictive PLS-SEM. The results were generally supportive of the proposed conceptual framework and all nine hypotheses were significant at the $P < 0.05$ level. The model's usefulness in comprehending the innovative marketing in the

**Table 6: Hypothesis testing results**

| Hypothesis | Structural relationship | Path coefficient (β) | t-value | P-value | Decision |
|---|---|---|---|---|---|
| $H_1$ | Artificial intelligence Chatbot quality→innovative marketing capability | 0.531 | 12.951 | <0.001 | Supported |
| $H_2$ | Artificial intelligence Chatbot quality→customer experience | 0.296 | 6.167 | <0.001 | Supported |
| $H_3$ | Customer trust→customer experience | 0.247 | 5.614 | <0.001 | Supported |
| $H_4$ | Perceived ease of use→customer experience | 0.281 | 5.979 | <0.001 | Supported |
| $H_5$ | Perceived ease of use→innovative marketing capability | 0.338 | 8.048 | <0.001 | Supported |
| $H_6$ | Customer experience→supply chain integration | 0.736 | 25.379 | <0.001 | Supported |
| $H_7$ | Supply chain integration→business performance | 0.462 | 11.55 | <0.001 | Supported |
| $H_8$ | Customer experience→business performance | 0.381 | 9.769 | <0.001 | Supported |
| $H_9$ | Artificial intelligence chatbot quality→customer experience→business performance (indirect effect) | 0.113 | 4.582 | <0.001 | Supported |

**Table 7: PLSpredict results**

| Endogenous construct | Indicator | PLS-RMSE | LM-RMSE | RMSE Difference (PLS−LM) | PLS-MAE | LM-MAE | MAE Difference (PLS−LM) | Predictive Performance |
|---|---|---|---|---|---|---|---|---|
| Innovative marketing capability | IMC1 | 0.642 | 0.681 | −0.039 | 0.491 | 0.516 | −0.025 | High |
| | IMC2 | 0.619 | 0.664 | −0.045 | 0.472 | 0.501 | −0.029 | High |
| | IMC3 | 0.628 | 0.672 | −0.044 | 0.478 | 0.509 | −0.031 | High |
| | IMC4 | 0.633 | 0.676 | −0.043 | 0.481 | 0.513 | −0.032 | High |
| Customer experience | CX1 | 0.596 | 0.641 | −0.045 | 0.451 | 0.482 | −0.031 | High |
| | CX2 | 0.603 | 0.648 | −0.045 | 0.456 | 0.487 | −0.031 | High |
| | CX3 | 0.611 | 0.657 | −0.046 | 0.463 | 0.494 | −0.031 | High |
| | CX4 | 0.599 | 0.643 | −0.044 | 0.452 | 0.483 | −0.031 | High |
| Supply chain integration | SCI1 | 0.582 | 0.624 | −0.042 | 0.439 | 0.468 | −0.029 | High |
| | SCI2 | 0.59 | 0.631 | −0.041 | 0.443 | 0.472 | −0.029 | High |
| | SCI3 | 0.587 | 0.629 | −0.042 | 0.441 | 0.47 | −0.029 | High |
| | SCI4 | 0.593 | 0.636 | −0.043 | 0.446 | 0.476 | −0.03 | High |
| Business performance | BP1 | 0.563 | 0.607 | −0.044 | 0.428 | 0.457 | −0.029 | High |
| | BP2 | 0.556 | 0.601 | −0.045 | 0.423 | 0.454 | −0.031 | High |
| | BP3 | 0.568 | 0.613 | −0.045 | 0.431 | 0.462 | −0.031 | High |
| | BP4 | 0.561 | 0.605 | −0.044 | 0.426 | 0.456 | −0.03 | High |

**Figure 4:** Importance–performance map analysis for business performance

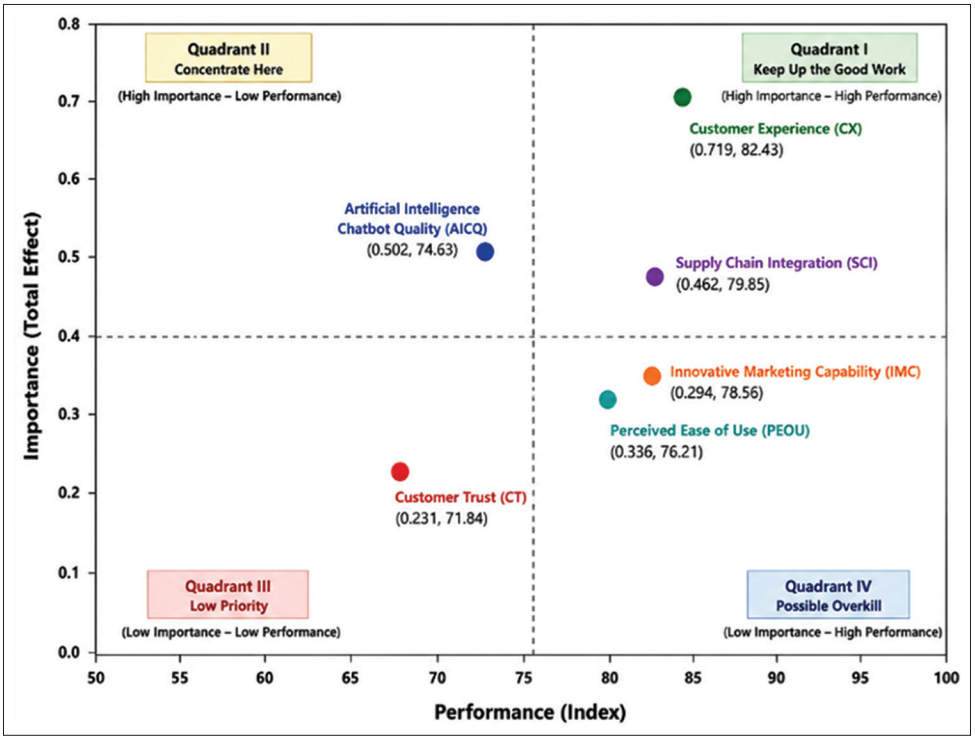



**Table 8a: Importance–performance map analysis results for business performance**

| Construct | Total Effect (Importance) | Performance Index | Priority Level | Managerial Action |
|---|---|---|---|---|
| Artificial intelligence chatbot quality (AICQ) | 0.502 | 74.63 | High | Improve chatbot intelligence, personalization, and response accuracy. |
| Customer trust (CT) | 0.231 | 71.84 | Medium | Strengthen privacy protection, security, and reliability. |
| Perceived ease of use (PEOU) | 0.336 | 76.21 | High | Simplify chatbot interface and enhance usability. |
| Innovative marketing capability (IMC) | 0.294 | 78.56 | Medium | Expand AI-driven personalized marketing initiatives. |
| Customer experience (CX) | 0.719 | 82.43 | Very High | Continue improving customer satisfaction and engagement through AI chatbots. |
| Supply chain integration (SCI) | 0.462 | 79.85 | High | Improve coordination, information sharing, and service responsiveness. |

**Table 8b: Ranking of constructs based on importance–performance map analysis**

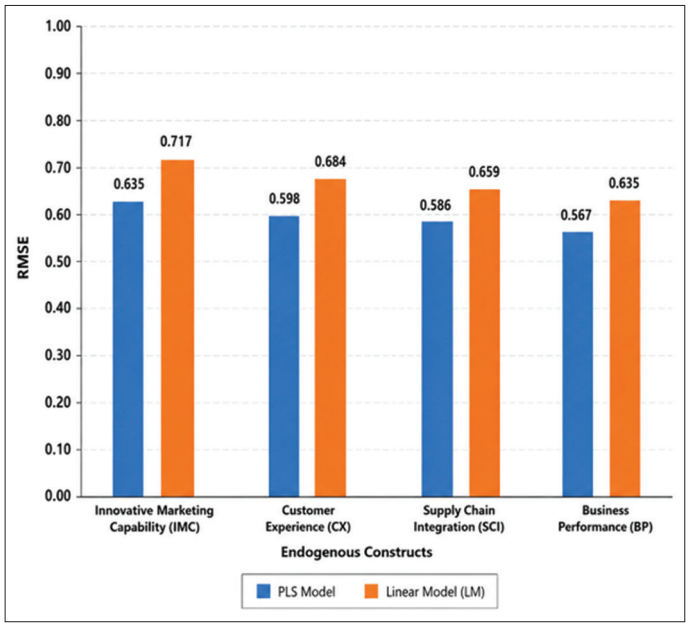
| Rank | Construct | Importance | Performance |
|---|---|---|---|
| 1 | Customer experience | 0.719 | 82.43 |
| 2 | Artificial intelligence chatbot quality | 0.502 | 74.63 |
| 3 | Supply chain integration | 0.462 | 79.85 |
| 4 | Perceived ease of use | 0.336 | 76.21 |
| 5 | Innovative marketing capability | 0.294 | 78.56 |
| 6 | Customer trust | 0.231 | 71.84 |

**Table 8c: Managerial priority matrix and recommended actions based on IPMA**

| Priority | Construct | Recommendation |
|---|---|---|
| Priority 1 | Customer experience | Enhance personalized interactions and customer satisfaction. |
| Priority 2 | Artificial Intelligence chatbot quality | Improve conversational intelligence, contextual understanding, and response quality. |
| Priority 3 | Supply chain integration | Strengthen cross-functional coordination and real-time information sharing. |
| Priority 4 | Perceived ease of use | Simplify chatbot navigation and interface design. |
| Priority 5 | Innovative marketing capability | Increase AI-driven personalization and campaign effectiveness. |
| Priority 6 | Customer trust | Enhance data security, transparency, and ethical AI practices. |

current business context was further validated by showing significant effectiveness for explaining and predicting, which indicated an appropriate model. The results showed that AI Chatbot Quality has a significant positive effect on Innovative Marketing Capability ($H_1$) and Customer Experience ($H_2$). The discovery suggests intelligent, responsive, and personalized chatbot systems can facilitate organizations to provide state-of-the-art marketing solutions and enhance customers' interactions with digital platforms. The findings align with prior research indicating that AI-powered conversational agents can be used to enable personalized communication, engaging with customers, and

**Figure 5:** PLSpredict results: Comparison of prediction errors between the PLS model and linear model




data-driven marketing strategies (Davenport et al., 2020; Huang and Rust, 2021; Rust and Huang, 2021). Quality chatbot services are therefore an essential capacity that boosts digital marketing efforts for organisations. The study also shows that customer trust ($H_3$) and perceived ease of use ($H_4$) are positively associated to customer experience. The results validate the assumptions of the technology acceptance model (Venkatesh et al., 2003; Venkatesh et al., 2012) which states that trustworthy and reliable technologies that are easy to use are more likely to be adopted by users.

The use of AI chatbot systems that deliver accurate information and are designed to protect customer privacy and that have intuitive interfaces can be linked to higher customer satisfaction and retention of customer technologies. The results showed that perceived ease of use had a positive influence on Innovative marketing capability ($H_5$), which implies that users' convenience of using AI applications has strengthened the users' ability to utilise and create personalized marketing strategies and engagement initiatives. The most positive relationship between all structural relationships was that between customer experience and supply chain integration ($H_6$). This discovery indicates that companies that are able to create more excellent customer experiences using artificial intelligence may benefit from better sharing, coordination, and collaboration among marketing, customer-service and supply-chain departments. AI chatbots can be used to enhance their role within the organization, as the data they generate from these customer interactions can be used to guide predictive customer service, real-time inventory management, and demand forecasting. The results are consistent with previous research that explores the importance of AI and digital technologies in enhancing supply chain visibility and operational efficiency (Wamba et al., 2020; Mikalef et al., 2021).

The study also validated the important role of supply chain integration ($H_7$) and customer experience ($H_8$) on improving business performance. The results demonstrate that AI-powered companies don't only excel at efficiency but at improving customer satisfaction and strengthening customer relationships as well. Using an integrated supply chain process helps to increase organization responsiveness, and customer experience enhances customer loyalty, repeat purchases and long-term competitiveness. The findings are in line with resource based view (RBV), which states that technological capabilities and organizational integration act as strategic resources that leads to SCA (Rai et al., 2019; Verhoef et al., 2021). Mediation analysis also indicated that the mediation of Customer Experience significantly mediated the relationship between AI Chatbot Quality and Business Performance ($H_9$). This discovery implies that the positives of AI Chatbot implementation are not just technological, but are mostly transcended to better organizational outcomes via better customer experiences. Therefore, companies should prioritize creating AI chatbots that can accommodate and offer customers customized experiences rather than only automating customer service tasks.

This study has grounded theory in an attempt to merge the two theoretical frameworks, the technology acceptance model (TAM) and the resource based view (RBV) into a single, predictive model. It illustrates the trans-classification of Customer Experience as a link between individual technology adoption and organizational performance, and how innovative marketing capability and supply chain integration further enhance the explanation power of TAM and RBV in AI-enabled marketing research. The insights offer useful recommendations for companies that want to use AI chatbots to enhance their marketing and operational results. AI Chatbot quality, customer experience, and supply chain integration are the areas that most impact business performance, so these aspects need to be strengthened. Reliability and a friendly, intelligent chatbot system can help to build customer engagement, thereby bolstering sustainable competitive advantage through investment. The results underscore the need to encourage responsible use of AI by setting regulations on data privacy, transparency, cybersecurity, and ethical AI governance for the benefit of the policy makers. Standardisation of AI frameworks and digital innovation policies can enable organisations to effectively implement trusted AI chatbot solutions and promote consumer trust, sustainable digital transformation, and resilience.

This study, although of theoretical and practical significance, has certain limitations. First, the cross sectional approach does not provide a causal linkage over time. Second, the results are self-reported, which could have response bias. Third, because purposive sampling was used, the results may not be applicable in other industries and locations. Longitudinal and cross cultural designs, probability sampling, objective organizational performance measures should be used in future research. Further moderators and mediators can be investigated, various types of AI like Generative AI and voice assistants can be compared and the framework can be cross-sector and cross-country validated in other business sectors.

## 6. CONCLUSION

The effect of the quality of the AI chatbot on the innovative marketing capability, customer experience, integration of the

supply chain and business performance is investigated in the present study following the Predictive PLS-SEM approach. The results showed that the quality of the AI chatbots, customer trust, and ease of use of the AI chatbots significantly affect innovative marketing and customer experience, both of which have a significant impact on supply chain integration and organizational performance. A mediation analysis also showed that the quality of the AI chatbots positively influences overall business performance via an effect on customer experience. The obtained PLSpredict and importance–performance map analysis (IPMA) scores confirmed the model's high predictive performance and that managerial focus needs to be on customer experience, AI chatbot quality, and supply chain integration.

The study adds to the literature by incorporating marketing, customer behavior and supply chain perspectives into a single predictive model based on technology acceptance model and resource-based view. From a business standpoint, adopting intelligent, trusted, and easy-to-use AI chatbots can bolster innovative marketing, boost customer satisfaction, enhance operational efficiency, and maintain sustainable business performance in the digital landscape. The study is one of the first predictive PLS models that combines the quality of AI Chatbot, innovative marketing potential, customer experience, supply chain integration, and business performance, advancing "explanatory" and "predictive" marketing research.

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