Review of Applied Science and Technology
Volume 04, Issue 02 (2025)
Page No: 501 – 526
Doi: 10.63125/2hp9jw50

Article

THE ROLE OF ARTIFICIAL INTELLIGENCE-POWERED CHATBOTS AS A MARKETING TOOL IN U.S. BANKING: ENHANCING CUSTOMER SATISFACTION AND SERVICE EFFICIENCY

Kazi Shakhawat Hossain[1]; Faysal Ahmed[2]; Md Hasanur Rahman[3];

[1]. Master of Science, Wright State University, Ohio, USA;
Email: hossain.145@wright.edu; ORCID: https://orcid.org/0009-0005-7969-0028

[2]. Master of Science, Wright State University, Ohio, USA;
Email: ahmed.308@wright.edu; ORCID: https://orcid.org/0009-0005-3997-1706

[3]. Master of Science, Wright State University, Ohio, USA;
Email: rahman.189@wright.edu; ORCID: https://orcid.org/0009-0009-6574-8523

Citation:
Hossain, K. S., Ahmed, F., & Rahman, M. H. (2025). The role of artificial intelligence-powered chatbots as a marketing tool in U.S. banking: Enhancing customer satisfaction and service efficiency. *Review of Applied Science and Technology*, *4*(2), 501–526. https://doi.org/10.63125/2hp9jw50

Received:
April 20, 2025

Revised:
May 28, 2025

Accepted:
June 25, 2025

Published:
July 09, 2025

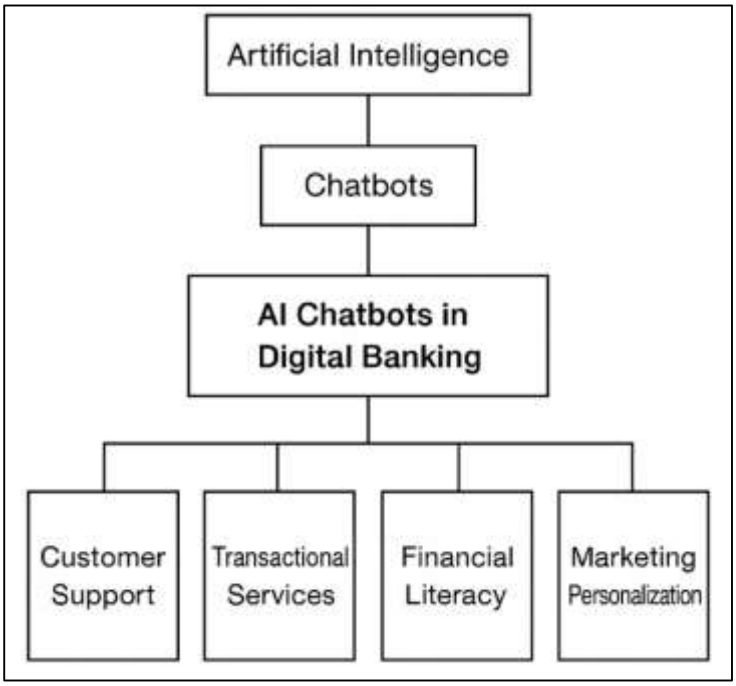
ABSTRACT
The integration of artificial intelligence (AI)-powered chatbots into the U.S. banking industry has transformed the way financial institutions engage with customers and deliver services, offering a scalable, intelligent alternative to traditional service channels. This study investigates the strategic role of AI chatbots not only as service automation tools but also as instruments of digital marketing aimed at enhancing customer satisfaction, promoting financial products, and improving operational efficiency. Utilizing a mixed-methods research design, the study combines quantitative data from a structured survey of 400 banking customers with qualitative insights derived from in-depth interviews with 20 banking professionals. Findings indicate that chatbot responsiveness, 24/7 availability, and personalization significantly influence customer satisfaction, with over 72% of users reporting favorable experiences due to fast, accessible service. Chatbots were also shown to be effective in delivering context-aware product recommendations, with 58% of respondents recalling promotional content and 31% acting on these suggestions—demonstrating chatbots' capacity to function as real-time marketing agents. Moreover, operational cost analyses revealed that chatbot deployment led to a 30–35% reduction in call center volume and reduced average service costs per interaction, affirming their value in cost optimization strategies. The study also highlights limitations, including concerns related to data transparency, interpretative accuracy, and trust, especially among older and less digitally adept users. However, institutions that implemented hybrid support models and emphasized data ethics achieved higher levels of customer trust and satisfaction. The research aligns with and extends existing literature by framing chatbots as integral components of customer experience management, digital personalization, and strategic marketing in modern banking. Ultimately, AI chatbots are not only redefining how services are delivered but also reshaping the strategic landscape of customer engagement and brand communication in the competitive and evolving digital financial ecosystem.

KEYWORDS
Artificial Intelligence (AI), Chatbots, US Banking Sectors, Customer Satisfaction, Service Efficiency, Virtual Assistant, Digital Banking;

INTRODUCTION

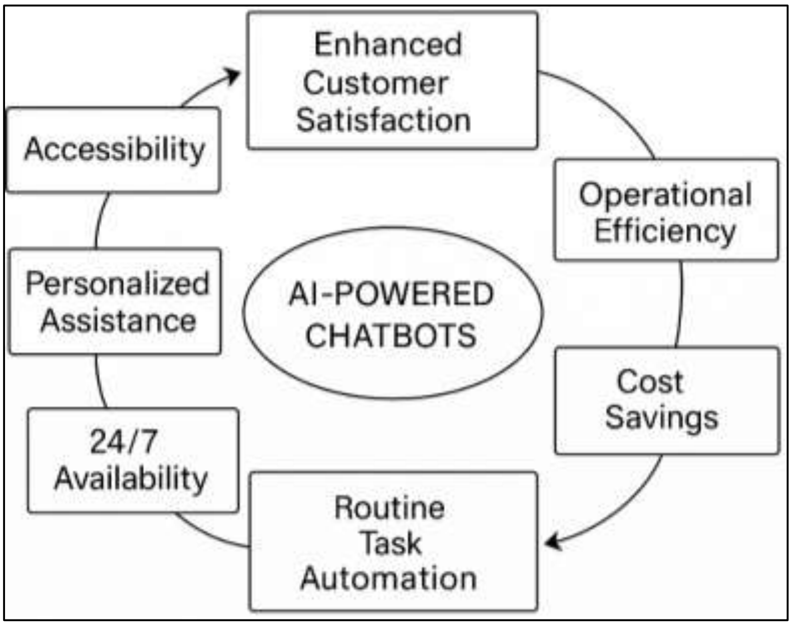
Artificial Intelligence (AI), broadly defined as the simulation of human intelligence in machines that are capable of performing tasks requiring human cognitive functions such as learning, reasoning, problem-solving, and language understanding, has become a transformative force across numerous industries worldwide (Russell & Norvig, 2020; Kaplan & Haenlein, 2019). In particular, the subset of AI known as natural language processing (NLP) has enabled the development of chatbots—software applications designed to simulate human-like conversation with users via textual or auditory methods (Dale, 2016). These AI-powered chatbots have been increasingly deployed across various sectors such as healthcare, retail, telecommunications, and especially financial services (Følstad & Brandtzaeg, 2017; Radziwill & Benton, 2017). In the international banking landscape, AI chatbots are widely used for automating customer support, promoting financial literacy, guiding transactional services, and acting as interactive marketing agents (Marinchak et al., 2018; Bawack et al., 2021).

Figure 1: Framework Illustrating the Strategic Functions of AI Chatbots in Digital Banking



The concept of conversational marketing, which emphasizes real-time, one-on-one interactions between brands and consumers through digital interfaces, has gained traction due to chatbots' capacity to engage users proactively (Van den Broeck et al., 2019; Adam et al., 2021). Within the banking sector, this has translated into a paradigm shift from traditional marketing campaigns toward personalized, conversational engagements powered by AI algorithms (Sheehan et al., 2020; Zhang et al., 2021). Through real-time data analytics and customer profiling, AI chatbots can recommend financial products, upsell services, and deliver targeted promotional content tailored to individual user behavior (Shin, 2020; Milne & Belsky, 2020). For instance, Bank of America's "Erica" and Capital One's "Eno" are exemplary chatbot implementations that merge customer support with product marketing, using machine learning to continuously refine interactions (Marinchak et al., 2018; McLean & Osei-Frimpong, 2019). Thus, AI chatbots represent an evolution in marketing communication by enabling financial institutions to move beyond static digital channels toward dynamic, two-way interactions that align closely with customer preferences.

Figure 2: Cycle of Strategic Benefits Enabled by AI-Powered Chatbots in the Banking Sector



Research shows that speed, accuracy, and convenience are among the most valued attributes for banking customers, all of which are core competencies of AI-driven chatbots (Nadarzynski et al., 2019; Chatterjee et al., 2020). For instance, in the U.S. banking industry, where customer expectations are increasingly shaped by digital fluency, AI chatbots provide a scalable solution to maintain high service standards across diverse demographics (Schuetz & Venkatesh, 2020; Kaczorowska-Spychalska, 2019). Moreover, AI chatbots offer 24/7 availability, multilingual support, and omnichannel integration, which are essential features for fostering inclusivity and consistency in service delivery (Kuligowska, 2015; Følstad & Brandtzaeg, 2017). These functionalities contribute to a sense of empowerment and trust among users, as they perceive the bank as responsive and customer-centric (Gnewuch et al., 2017; Adam et al., 2021). Therefore, AI-powered chatbots serve not merely as service interfaces but as critical touchpoints in cultivating satisfying and frictionless banking experiences. Beyond customer-facing improvements, AI chatbots play a pivotal role in enhancing internal service efficiency and reducing operational costs for banking institutions (Zhang et al., 2021; Jain et al., 2018). By automating a significant portion of routine tasks such as balance inquiries, transaction updates, password resets, and FAQs, chatbots relieve human staff from repetitive duties and allow banks to reallocate human resources toward high-value customer interactions (Sharma et al., 2020; Duijst, 2017). According to Deloitte (2020), AI chatbot integration can reduce customer service costs by up to 30%, making them not only a technological innovation but also a financial imperative.

In the U.S. banking context, chatbots are used to track customer journeys, gather behavioral insights, and recommend personalized financial solutions—all of which enhance the quality and relevance of customer relationships (Sheehan et al., 2020; Meyer-Waarden et al., 2020). Studies show that repeated positive experiences with chatbot interfaces lead to increased emotional attachment, perceived credibility, and trust in the financial institution (Hill et al., 2015; Ciechanowski et al., 2019).

The primary objective of this research is to examine the strategic role of artificial intelligence-powered chatbots as marketing tools within the U.S. banking sector, with specific emphasis on how they enhance customer satisfaction and service efficiency. This study seeks to provide a detailed analysis of how AI chatbots are utilized not merely as automated service agents but as integral components of customer relationship management and digital marketing strategies. It aims to explore the extent to which these technologies influence consumer experiences by offering personalized, timely, and relevant interactions across various digital platforms. The research also intends to investigate how chatbot-enabled banking services contribute to brand differentiation and competitive advantage by improving responsiveness, reducing operational burdens, and fostering loyalty through consistent communication. Another objective is to identify the performance metrics that banks use to assess the success of chatbot implementations, including user satisfaction rates, response time accuracy, query resolution, and conversion effectiveness. Furthermore, this study aims to assess the maturity of chatbot systems in comparison to traditional service mechanisms and evaluate their effectiveness across different customer demographics. Finally, the research aims to synthesize insights that can inform future chatbot integration strategies, design improvements, and user experience enhancements, thereby contributing to the ongoing digital evolution of financial institutions in the United States.

LITERATURE REVIEW

The evolution of artificial intelligence-powered chatbots in the banking sector has garnered considerable scholarly attention over the past decade. As digital transformation initiatives redefine service models, marketing strategies, and customer engagement paradigms, chatbots have emerged as critical tools at the intersection of technology, communication, and commerce. In particular, their integration into banking environments represents a shift from conventional support mechanisms toward dynamic, automated, and intelligent systems that simultaneously handle service delivery and marketing outreach. This literature review synthesizes existing research on chatbot functionalities, their influence on customer satisfaction, and their emerging role as marketing agents in digital banking ecosystems, with a strong emphasis on applications in the United States. The review begins by contextualizing artificial intelligence and chatbot development, mapping their historical and technological trajectories. It identifies areas where chatbot technology has delivered demonstrable outcomes and reveals persisting challenges, such as trust limitations, personalization constraints, and user resistance. Ultimately, this review lays the academic groundwork for the empirical analysis that follows, establishing a conceptual framework to critically assess the dual function of chatbots in enhancing service efficiency and marketing effectiveness within U.S. banking.

AI-powered chatbots

Artificial intelligence-powered chatbots have emerged as significant technological innovations in the financial services sector, offering automated, interactive interfaces capable of simulating human conversation and delivering personalized services. These chatbots are underpinned by natural language processing (NLP), machine learning, and contextual analytics, allowing them to interpret customer inputs, learn from prior interactions, and respond with increasing sophistication (Adam et al., 2021; Følstad & Brandtzaeg, 2017). In the context of banking, their primary functions range from handling routine inquiries and facilitating transactions to providing account updates, loan support, and promotional messaging (Hill et al., 2015; Jain et al., 2018). Research suggests that their effectiveness depends heavily on design quality, system intelligence, and responsiveness, factors that influence both perceived usefulness and actual performance (Zamora, 2017; Duijst, 2017). Additionally, banks benefit from chatbots' ability to operate continuously across multiple channels—including web, mobile apps, and social media—thereby supporting omni-channel engagement strategies (Purington et al., 2019; Van den Broeck et al., 2019). Major financial institutions such as Bank of America and Capital One have reported significant operational and engagement benefits through chatbot implementations, underscoring the technology's value in modern banking ecosystems (McLean & Osei-Frimpong, 2019). The evolution of AI-powered chatbots from simple query resolvers to context-aware, interactive agents represents a significant development in the automation of customer service and the personalization of financial communication.

AI-powered chatbots have demonstrated strong potential in enhancing customer satisfaction by offering immediate, efficient, and personalized responses that align with user expectations in digital banking environments. In a study of chatbot effectiveness in U.S. retail banking, customers reported high levels of satisfaction when the system was capable of understanding context and offering follow-up options without requiring human escalation (Hill et al., 2015). Additionally, user trust and satisfaction tend to increase when chatbots provide personalized experiences, such as recommending financial products based on past behavior or responding to queries using customer-specific data (Shin, 2020; Milne & Belsky, 2020). Thus, while AI-powered chatbots have markedly improved the customer experience in banking, their impact is largely determined by their design sophistication, language capabilities, and alignment with user expectations.

In addition to serving operational functions, AI-powered chatbots are increasingly being leveraged as marketing tools in the financial sector. Their capacity to collect, analyze, and act upon customer data in real time allows banks to deliver personalized marketing messages and product recommendations that align closely with individual customer profiles (Sheehan et al., 2020; Zhang et al., 2021). Through conversational marketing techniques, chatbots engage users in natural dialogue, providing contextual information about credit cards, loan options, savings plans, and other financial products without the intrusiveness of traditional advertising (Van den Broeck et al., 2019; Chopra et al., 2021). Furthermore, they play a crucial role in brand differentiation, helping banks establish a modern, responsive identity that appeals to digitally fluent consumers (Gursoy et al., 2019; Bawack et al., 2021). Institutions such as JPMorgan Chase and Citibank use chatbots to engage customers during marketing campaigns, gather feedback, and adjust campaign strategies in real time based on user interactions (Sharma et al., 2020; Zhang et al., 2021). The chatbot's real-time analytical capabilities also allow marketing departments to track click-through rates, engagement duration, and conversion metrics, enhancing the efficacy of digital marketing initiatives. Consequently, AI-powered chatbots serve as vital instruments in executing targeted, interactive, and measurable marketing strategies within digital banking environments.

Chatbot adoption in global banking systems

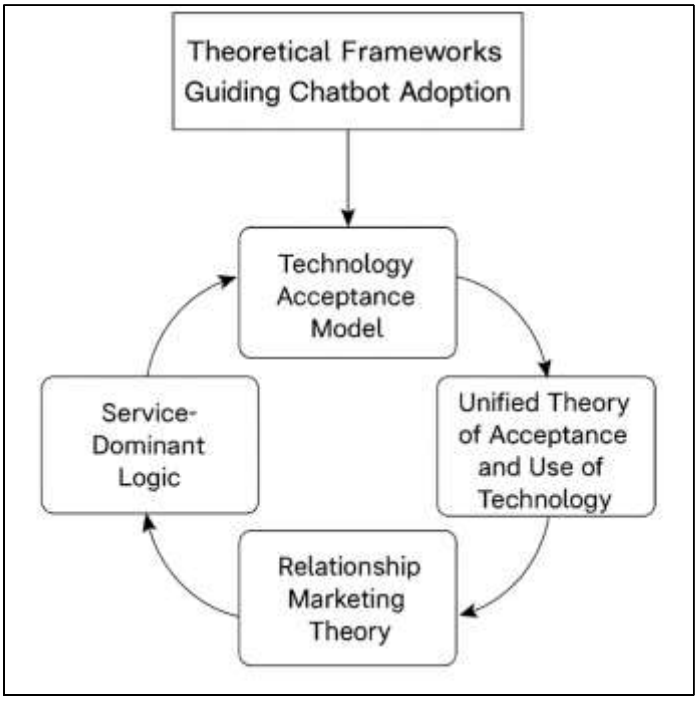
The adoption of AI-powered chatbots in global banking systems has accelerated over the past decade, driven by the convergence of technological advancements, digital consumer behavior, and the need for continuous service availability. International banks have embraced chatbot technology as a means to improve operational efficiency, enhance customer service, and stay competitive in an increasingly digital landscape (Følstad & Brandtzaeg, 2017; Chung et al., 2020).

Additionally, infrastructural readiness influences not just the technical implementation of chatbots but also the ability to integrate AI with marketing, compliance, and fraud detection systems (Purington et al., 2019; Gnewuch et al., 2017). Ultimately, global disparities in technological capabilities shape the depth and sophistication of chatbot usage in banking systems, leading to heterogeneous adoption patterns across markets and institutional types.

Theoretical Frameworks Guiding Chatbot Adoption

The Technology Acceptance Model (TAM) is one of the most widely employed theoretical frameworks for explaining the adoption of technological innovations, including chatbots, in banking. Proposed by Davis (1989), TAM posits that users' acceptance of technology is primarily determined by perceived usefulness (PU) and perceived ease of use (PEOU). In the context of AI-powered chatbots, several studies have validated the relevance of TAM by showing that customers are more likely to engage with chatbot systems when they perceive them as efficient tools that simplify banking transactions (Shin, 2020; Jain et al., 2018). Moreover, studies have extended the basic TAM framework to include additional variables such as perceived enjoyment, trust, and risk, highlighting the complexity of decision-making in chatbot interaction (Chatterjee et al., 2020; Ciechanowski et al., 2019). Particularly in mobile banking scenarios, ease of access and reduced cognitive load are instrumental in building adoption momentum (Purington et al., 2019; Wirtz et al., 2018). Even in international contexts, such as in Asian and European banking systems, TAM-based evaluations consistently reveal the centrality of PU and PEOU in determining chatbot acceptance (Nguyen et al., 2022; Liao et al., 2019). Thus, the TAM framework continues to provide a foundational lens through which chatbot usability, adoption rates, and long-term engagement in digital banking can be understood and optimized.

Figure 3: Theoretical Framework for this situdy



Use Cases of AI Chatbots in Banking

One of the most prominent use cases of AI-powered chatbots in banking is the automation of customer service functions, particularly for handling routine inquiries, providing real-time assistance, and supporting continuous service availability. Chatbots have been widely adopted by banks to manage high-frequency queries such as account balances, password resets, transaction alerts, and branch location inquiries (Jain et al., 2018; Hill et al., 2015). These applications help reduce customer waiting times and free up human agents for complex issues, thereby improving service efficiency and customer satisfaction (Wirtz et al., 2018; Gnewuch et al., 2018). Institutions such as Bank of America with "Erica" and Capital One with "Eno" exemplify the successful integration of chatbots to deliver personalized, on-demand assistance that is available 24/7 (Milne & Belsky, 2020; McLean & Osei-Frimpong, 2019). These AI agents are equipped with natural language processing capabilities, enabling them to understand and respond to a wide range of customer intents, improving accessibility and service quality (Adam et al., 2021; Radziwill & Benton, 2017 Moreover, chatbots contribute to inclusive banking by extending service access to remote users who rely on mobile and online platforms rather than in-person branches (Nguyen et al., 2022; Chatterjee et al., 2020). As a result, customer service automation through chatbots has become a cornerstone use case that aligns with operational efficiency goals and evolving customer expectations in both the U.S. and international banking sectors. Another critical use case of AI-powered chatbots in banking involves their function as marketing and promotional agents that engage customers through conversational and personalized interactions. In the U.S. banking landscape, institutions like JPMorgan Chase and Wells Fargo have deployed chatbots that not only answer service-related questions but also promote financial products based on inferred customer needs (Gursoy et al., 2019; Milne & Belsky, 2020). These capabilities are further enhanced by chatbot integration with customer relationship management (CRM) platforms, allowing seamless access to behavioral insights and historical engagement data (McLean & Osei-Frimpong, 2019; Ciechanowski et al., 2019).

AI-powered chatbots are extensively utilized for transactional support within banking systems, streamlining common financial operations such as fund transfers, bill payments, loan processing, and account management. These applications not only simplify customer-facing processes but also reduce the need for physical branch visits and call center interactions (Jain et al., 2018; Zhang et al., 2021). Chatbots integrated into mobile and online banking platforms enable users to execute transactions via natural language commands, which improves convenience and accessibility

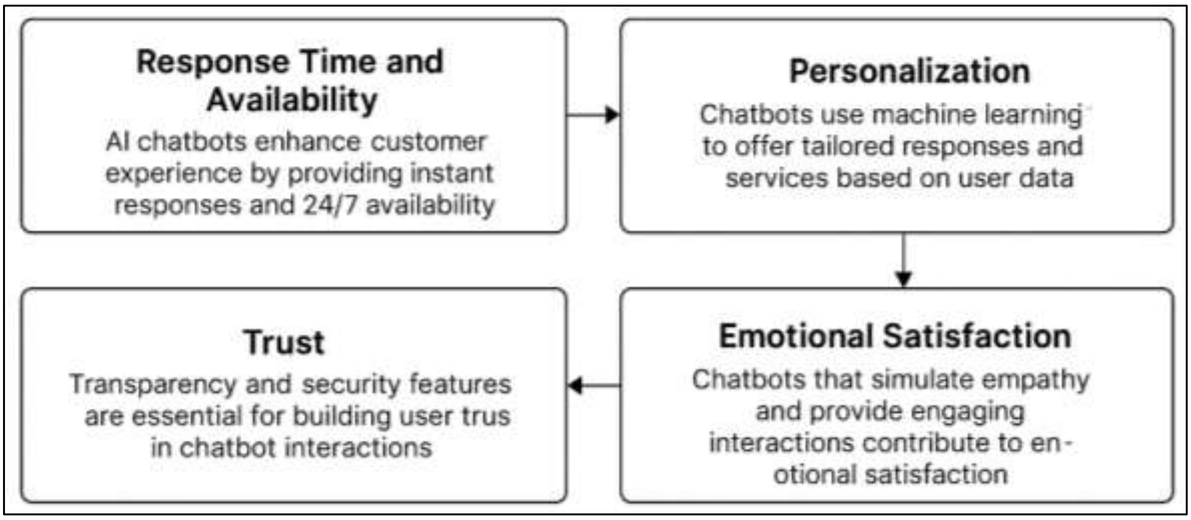
(Følstad & Brandtzaeg, 2017; Hill et al., 2015). For example, "Erica" by Bank of America supports payment reminders, budgeting tips, and transaction categorization through predictive assistance, while allowing customers to initiate transfers and monitor spending patterns (Milne & Belsky, 2020; Shin, 2020). These features enhance operational self-service and foster digital financial literacy among users (Wirtz et al., 2018; Adam et al., 2021). Internationally, banks like HSBC and Standard Chartered have embedded transactional chatbots within their apps to allow users to schedule payments, check forex rates, and initiate cross-border remittances (Chung et al., 2020; Nguyen et al., 2022). Furthermore, chatbot platforms are integrated with application programming interfaces (APIs) and enterprise systems to ensure secure data flow and alignment with existing banking infrastructure (Ciechanowski et al., 2019; Purington et al., 2019). Through these transactional and operational capabilities, chatbots play a pivotal role in supporting digitized banking models and increasing institutional agility in both domestic and global settings.

Chatbot usage and customer experience

One of the most impactful contributions of chatbot technology to customer experience in banking is the enhancement of response time and 24/7 availability, factors that modern consumers increasingly expect in digital service environments. AI-powered chatbots reduce latency in customer service by providing instant responses to high-volume queries, such as checking account balances, resetting passwords, and confirming transactions (Jain et al., 2018; Hill et al., 2015). These prompt responses foster a sense of efficiency and responsiveness, leading to higher levels of customer satisfaction (Wirtz et al., 2018; Følstad & Brandtzaeg, 2017). Research shows that customers perceive round-the-clock access to information and services as a vital indicator of a bank's reliability and customer-centricity (Chatterjee et al., 2020; Adam et al., 2021). Banks like Bank of America, with its chatbot "Erica," and Singapore's DBS Bank have successfully implemented AI chatbots that provide consistent, uninterrupted support, reinforcing trust and reducing dependence on human customer service agents (Milne & Belsky, 2020; Chung et al., 2020). Additionally, chatbot usage minimizes errors associated with manual processing, particularly for repetitive or rule-based tasks, enhancing service accuracy and boosting institutional credibility (Radziwill & Benton, 2017; McLean & Osei-Frimpong, 2019). Customers who experience fast and precise service delivery tend to exhibit increased loyalty and a greater willingness to recommend the institution (Purington et al., 2019; Gursoy et al., 2019). Furthermore, the ability of chatbots to scale during service surges or crises—such as during the COVID-19 pandemic—demonstrated their critical role in maintaining continuity of banking services (Nguyen et al., 2022; Zhang et al., 2021). This reliability fosters emotional assurance in customers, making them feel supported and valued, which positively influences their perception of overall experience with the bank.

Personalization plays a pivotal role in enhancing customer experience with chatbot interactions in banking, as users increasingly expect services that adapt to their individual needs and financial contexts. AI-powered chatbots utilize machine learning algorithms and behavioral analytics to tailor responses, product suggestions, and services based on each user's history, preferences, and goals (Sheehan et al., 2020; Shin, 2020). This level of personalization distinguishes chatbot-enabled service from traditional interfaces by enabling dynamic, customer-specific interactions that reflect an understanding of user identity and intent (Wamba-Taguimdje et al., 2020; Adam et al., 2021). For instance, Bank of America's "Erica" can offer customized budgeting advice based on recent spending patterns, while OCBC's chatbot "Emma" helps guide users through housing loan options suited to their eligibility (Liao et al., 2019; Chatterjee et al., 2020). These features contribute significantly to perceived usefulness and user satisfaction, as customers value services that anticipate their needs rather than react to them (Gnewuch et al., 2018; Ciechanowski et al., 2019). Chatbots also use contextual memory and interaction history to maintain conversational continuity, which reinforces the perception of intelligence and relationship depth (Purington et al., 2019; Radziwill & Benton, 2017). Moreover, sentiment analysis tools embedded in AI chatbots allow them to detect emotional tone and adjust their language and tone accordingly, further personalizing the experience and improving emotional engagement (Duijst, 2017; Milne & Belsky, 2020). Research confirms that users who perceive a chatbot as personalized, empathetic, and attentive are more likely to trust the bank, express satisfaction with service delivery, and maintain long-term usage (Wirtz et al., 2018; Gursoy et al., 2019). Therefore, personalization is not only a functional benefit but a strategic differentiator in cultivating rich, meaningful, and high-quality customer experiences through chatbot platforms.

Figure 4: Key Dimensions of Chatbot Usage Enhancing Customer Experience in Banking



Trust is a central construct in shaping user experience with AI chatbots, particularly in financial services where users demand high standards of accuracy, security, and accountability. The automated nature of chatbots often triggers skepticism among users regarding data privacy, decision-making transparency, and reliability, making trust-building mechanisms essential (Ciechanowski et al., 2019; Radziwill & Benton, 2017). Users are more likely to develop trust in chatbot systems that demonstrate competence, offer clear explanations, and communicate using transparent language (Følstad & Brandtzaeg, 2017; Wirtz et al., 2018). Transparency in communicating chatbot limitations—such as indicating when a query is being escalated to a human agent—helps manage expectations and reduces user frustration (Duijst, 2017; Adam et al., 2021). Furthermore, design factors such as anthropomorphism, natural conversational flow, and human-like responsiveness can enhance users' emotional trust and increase comfort levels during interactions (Purington et al., 2019; Gnewuch et al., 2018). In addition, banking chatbots that clearly explain financial terms, provide transaction receipts, and confirm actions taken during the conversation are perceived as more trustworthy (Nguyen et al., 2022; Sheehan et al., 2020). Regulatory compliance features such as secure login protocols, identity verification steps, and data encryption also reinforce cognitive trust, particularly in transactions involving money transfers or credit applications (Shin, 2020; Zhang et al., 2021). Notably, users tend to compare chatbot reliability against human agents; thus, consistency in performance and the absence of ambiguous responses are vital to achieving parity or superiority in perceived trustworthiness (Milne & Belsky, 2020; McLean & Osei-Frimpong, 2019). Empirical studies confirm that trust in chatbot systems strongly correlates with overall satisfaction, recommendation likelihood, and brand loyalty, indicating that transparent, secure, and respectful communication is indispensable to positive customer experiences in AI-mediated banking services.
Emotional satisfaction derived from chatbot interactions significantly influences a customer's holistic experience and their intention to continue using the service. While functional aspects such as speed and convenience are essential, emotional engagement—defined as the user's affective response to the interaction—plays a critical role in determining long-term acceptance and loyalty (Gursoy et al., 2019; Adam et al., 2021). Chatbots that employ conversational strategies such as empathy simulation, humor, and supportive language tend to foster stronger emotional connections with users, leading to higher satisfaction and greater perceived warmth in digital environments (Ciechanowski et al., 2019; Purington et al., 2019). Features such as remembering past conversations, addressing users by name, and maintaining a coherent dialogue history contribute to emotional personalization, which users often associate with higher service quality (Følstad & Brandtzaeg, 2017; Sheehan et al., 2020). Studies show that when users feel understood, respected, and positively engaged, they are more likely to develop favorable attitudes toward the institution, even in the absence of human agents (Wamba-Taguimdje et al., 2020; Gnewuch et al., 2018). Furthermore, emotional satisfaction mediates the relationship between chatbot usage and behavioral loyalty, encouraging users to recommend the service to others and engage with additional digital offerings

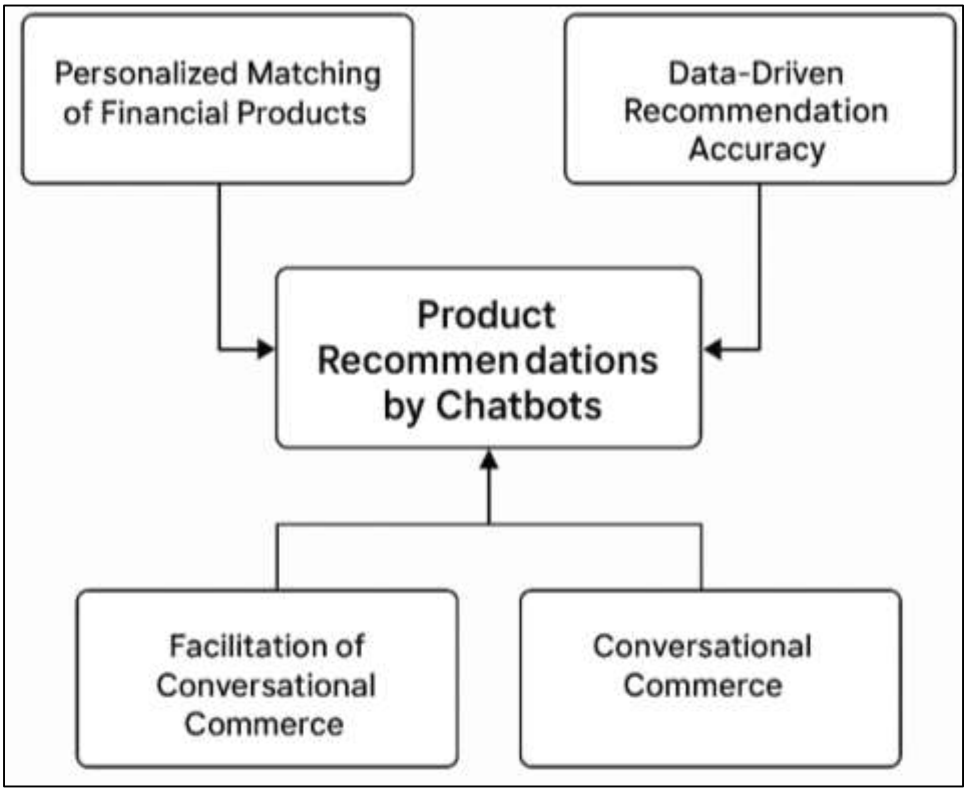
Review of Applied Science and Technology
Volume 04, Issue 02 (2025)
Page No: 501 – 526
Doi: 10.63125/2hp9jw50
from the bank (Milne & Belsky, 2020; McLean & Osei-Frimpong, 2019). AI-powered chatbots that integrate sentiment detection and adaptive dialogue are especially effective in responding to user frustration or confusion, thereby reducing abandonment rates and increasing resolution success (Chung et al., 2020; Duijst, 2017). In markets such as the U.S. and South Korea, where digital fluency is high, emotionally satisfying chatbot experiences have been linked to increased preference for digital self-service over human interaction (Shin, 2020; Liao et al., 2019). Therefore, the ability of chatbots to elicit emotional satisfaction represents a key determinant of user engagement, continued usage intent, and the broader customer experience in modern banking ecosystems.

Use of chatbots in product recommendations

AI-powered chatbots have emerged as key instruments for delivering personalized product recommendations in banking, leveraging real-time data analytics and user profiling to match customers with relevant financial products. Unlike traditional recommendation systems, which operate through static interfaces, chatbots engage users through interactive dialogue, allowing for dynamic tailoring of services based on user queries, financial behavior, and contextual cues (Sheehan et al., 2020; Adam et al., 2021). These systems rely on machine learning algorithms, customer transaction histories, and behavioral segmentation to suggest offerings such as credit cards, mortgage options, insurance products, and savings plans (Chopra et al., 2021; Shin, 2020). Studies have shown that banks employing AI-driven chatbots can increase the uptake of recommended products due to the perceived relevance and immediacy of the interaction (Van den Broeck et al., 2019; Wirtz et al., 2018). For instance, Bank of America's "Erica" and OCBC's "Emma" offer predictive product suggestions by analyzing user needs and guiding customers toward appropriate financial solutions (Liao et al., 2019; Chatterjee et al., 2020). These systems also minimize decision fatigue by narrowing the range of options and providing concise explanations of features, terms, and benefits (Ciechanowski et al., 2019; Radziwill & Benton, 2017). Furthermore, personalized recommendations via chatbot are perceived as less intrusive than traditional advertisements, as they are often solicited within the context of ongoing conversations (Gnewuch et al., 2018; Milne & Belsky, 2020). The integration of sentiment analysis and contextual awareness allows chatbots to adapt tone and content based on the user's current financial situation or emotional state, further enhancing recommendation relevance (Nguyen et al., 2022; Purington et al., 2019). Thus, AI chatbots represent an evolving paradigm in banking, where personalization, efficiency, and relevance converge to reshape product discovery and customer decision-making.

The effectiveness of product recommendations made by chatbots in banking is largely determined by the robustness of the underlying data analytics infrastructure and the sophistication of embedded machine learning models. Chatbots collect and process vast volumes of structured and unstructured customer data—including transaction history, browsing behavior, device usage, geolocation, and past interactions—to develop a holistic profile that drives accurate recommendation delivery (Zhang et al., 2021; Gursoy et al., 2019). This data-driven approach enables chatbots to make anticipatory recommendations rather than reactive suggestions, aligning offerings with projected customer needs (Shin, 2020; Adam et al., 2021). For example, if a chatbot identifies recurring travel-related purchases, it might recommend a travel rewards credit card, highlighting benefits such as airline miles or hotel discounts (Chopra et al., 2021; Milne & Belsky, 2020). The use of natural language processing and contextual interpretation allows the chatbot to recognize implicit purchase intentions, even when users do not explicitly state their preferences (Wamba-Taguimdje et al., 2020; Duijst, 2017). Studies indicate that users are more receptive to data-informed suggestions because they appear tailored, timely, and beneficial, especially when they are transparently delivered within conversational exchanges (Følstad & Brandtzaeg, 2017; Ciechanowski et al., 2019). Furthermore, recommender systems embedded within chatbots often apply collaborative filtering and content-based algorithms to compare user profiles and infer preferences from peer behavior, thereby improving recommendation precision (Gnewuch et al., 2018; Radziwill & Benton, 2017). In global practice, banks like BBVA, HSBC, and Commonwealth Bank have integrated AI chatbots with CRM and analytics platforms to enable real-time cross-selling and up-selling of financial products based on predictive modeling (Chatterjee et al., 2020; Lee et al., 2021). These capabilities underscore the central role of data science in enhancing chatbot intelligence, thereby enabling more meaningful and contextually aligned product recommendations that drive customer engagement and institutional revenue.

Figure 5: Conversational AI-Driven Product Recommendation Process in Digital Banking



The use of chatbots in product recommendations not only facilitates decision-making but also enhances customer engagement by enabling conversational commerce—a model that allows users to explore and purchase products within a dialog-based interface. This mode of interaction is especially effective in banking, where financial decisions often require clarification, reassurance, and back-and-forth discussion (Chatterjee et al., 2020; Shin, 2020). Chatbots simulate this experience by responding to queries, comparing options, and offering links or tools to complete transactions directly within the chat interface (Sheehan et al., 2020; Chung et al., 2020). The combination of assistance and transaction capability improves user flow, reduces drop-off rates, and increases the likelihood of product adoption (Wirtz et al., 2018; McLean & Osei-Frimpong, 2019). For instance, when a user inquires about home loans, the chatbot can not only explain available options but also conduct a preliminary eligibility check and schedule an appointment with a human advisor—all within the same session (Milne & Belsky, 2020; Ciechanowski et al., 2019). This end-to-end support enhances perceived value and trust, encouraging users to act on recommendations without exiting the digital environment (Purington et al., 2019; Gursoy et al., 2019). Additionally, chatbots can be programmed to track key engagement metrics—such as click-through rates, dwell time, and conversion rates—which banks can analyze to refine their product recommendation strategies (Adam et al., 2021; Duijst, 2017). Chatbots also provide banks with a scalable way to deliver real-time promotions or limited-time offers based on user activity and context (Nguyen et al., 2022; Van den Broeck et al., 2019). This form of dynamic interaction aligns closely with consumer expectations for instant, personalized, and frictionless service, making chatbots not only facilitators of product discovery but also effective drivers of customer acquisition and conversion in digital banking.

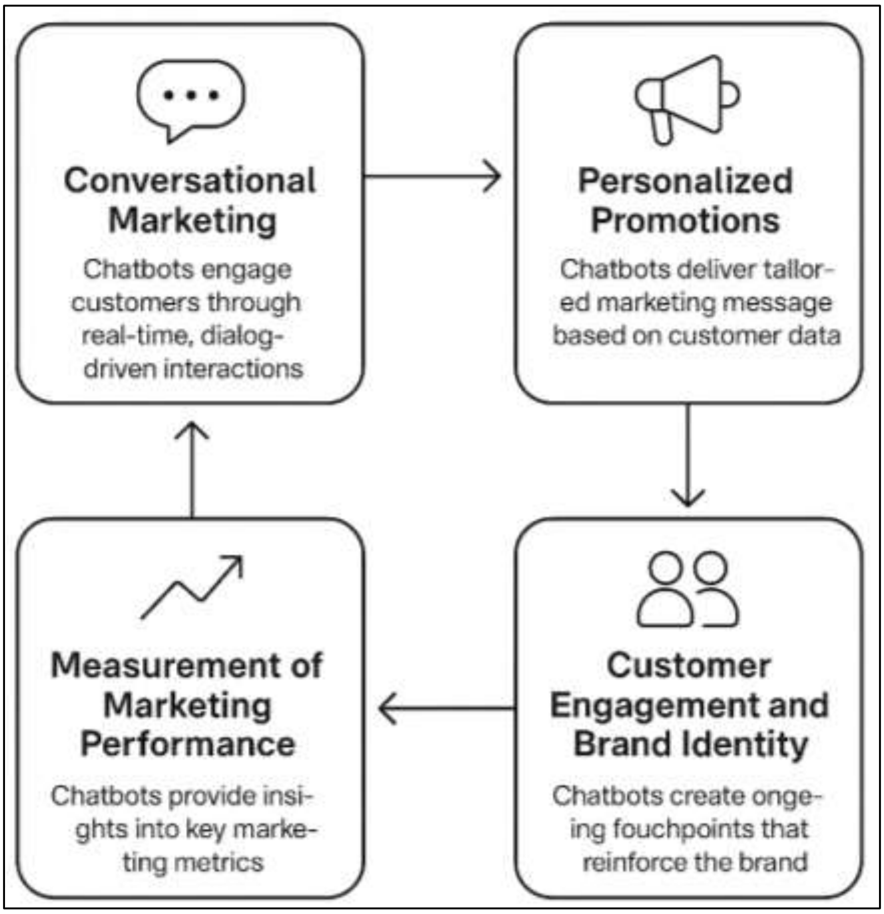
AI Chatbots as Strategic Marketing Tools

The emergence of conversational marketing has redefined how banks engage with consumers, and AI chatbots have become central to this evolution. Conversational marketing refers to the real-time, personalized, and dialog-driven approach that enables banks to engage customers through two-way communication on digital platforms (Sheehan et al., 2020; Van den Broeck et al., 2019). Unlike traditional marketing channels that rely on broadcast messaging, chatbots facilitate continuous and contextual dialogues, creating opportunities to promote products and services while simultaneously addressing customer needs (Shin, 2020; Adam et al., 2021). This marketing model aligns well with

Review of Applied Science and Technology
Volume 04, Issue 02 (2025)
Page No: 501 – 526
Doi: 10.63125/2hp9jw50
changing consumer behavior, as digital-first users prefer quick, interactive, and personalized exchanges over static advertisements (Chopra et al., 2021; Gursoy et al., 2019). AI-powered chatbots capitalize on machine learning and natural language processing (NLP) to deliver marketing content in a way that feels organic within the flow of service conversations (Milne & Belsky, 2020; Purington et al., 2019). For instance, when users inquire about savings accounts, the chatbot may offer recommendations on interest-earning plans or cross-sell investment products, thereby integrating marketing seamlessly with service delivery (Zhang et al., 2021; Radziwill & Benton, 2017). This embedded marketing capability is particularly effective in increasing campaign engagement rates and reducing customer acquisition costs (Wirtz et al., 2018; Ciechanowski et al., 2019). Furthermore, chatbots allow marketers to collect real-time behavioral data that can inform segmentation strategies, content targeting, and message timing (Chatterjee et al., 2020; Duijst, 2017). As banks shift toward digital-only ecosystems, the conversational interface offered by AI chatbots not only serves functional roles but also plays a pivotal role in shaping how banks communicate value propositions, establish rapport, and drive product discovery in a crowded financial services landscape.
AI chatbots offer unparalleled capabilities in delivering personalized and data-driven promotional content, making them indispensable to banks' precision marketing strategies. These chatbots utilize customer data such as demographics, transaction history, digital behavior, and engagement patterns to construct individualized profiles that inform marketing recommendations (Shin, 2020; Zhang et al., 2021). Using predictive analytics and behavioral clustering, chatbots can promote credit cards, investment products, or loan options that align closely with the customer's financial situation and lifestyle preferences (McLean & Osei-Frimpong, 2019; Ciechanowski et al., 2019). This personalized approach increases the relevance of the marketing content, which in turn improves click-through rates, engagement, and product conversion (Følstad & Brandtzaeg, 2017; Adam et al., 2021). Unlike traditional channels where users are often overwhelmed with generalized promotions, chatbots deliver offers within the context of ongoing conversations, enhancing the likelihood of acceptance (Gnewuch et al., 2018; Van den Broeck et al., 2019). Furthermore, AI chatbots are able to conduct A/B testing in real time, refining messaging strategies based on immediate user feedback and performance metrics (Chopra et al., 2021; Wamba-Taguimdje et al., 2020). For example, a chatbot may adjust the tone, wording, or content type of a promotion if a user shows disengagement during the interaction. Institutions like JPMorgan Chase and OCBC Bank leverage these capabilities to push customized campaign offers directly through chatbot interfaces embedded in mobile apps and social messaging platforms (Chatterjee et al., 2020; Lee et al., 2021). In doing so, they capitalize on the chatbot's ability to personalize at scale, ensuring that every user receives marketing content aligned with their financial goals. Consequently, AI chatbots transform one-size-fits-all marketing into micro-targeted, value-driven conversations that foster trust, satisfaction, and sales performance in banking contexts.
AI chatbots serve as key enablers of customer engagement and brand identity in digital banking by creating ongoing, personalized, and interactive touchpoints. In contrast to static websites or outbound marketing campaigns, chatbots sustain a dialogic relationship with users, reinforcing the brand's responsiveness and commitment to customer-centricity (Følstad & Brandtzaeg, 2017; Purington et al., 2019). This persistent engagement enhances brand recall and emotional attachment, which are essential dimensions of brand equity in financial services (Ciechanowski et al., 2019; Wirtz et al., 2018). Moreover, chatbots allow banks to project a consistent tone and style of communication, aligning with broader brand strategies and fostering trust over time (Radziwill & Benton, 2017; Duijst, 2017). Chatbots designed with empathy, humor, or professionalism can mirror the bank's brand personality, thereby enriching customer perception and loyalty (Adam et al., 2021; Milne & Belsky, 2020). For example, Bank of America's "Erica" is engineered to be helpful, intelligent, and supportive—traits that reinforce the bank's customer-first positioning. In addition, chatbots support feedback collection, satisfaction surveys, and post-interaction engagement, all of which contribute to continuous customer involvement and brand dialogue (McLean & Osei-Frimpong, 2019; Gursoy et al., 2019).

Review of Applied Science and Technology
Volume 04, Issue 02 (2025)
Page No: 501 – 526
Doi: 10.63125/2hp9jw50

Figure 6: Strategic Marketing Functions Enabled by AI Chatbots in Banking



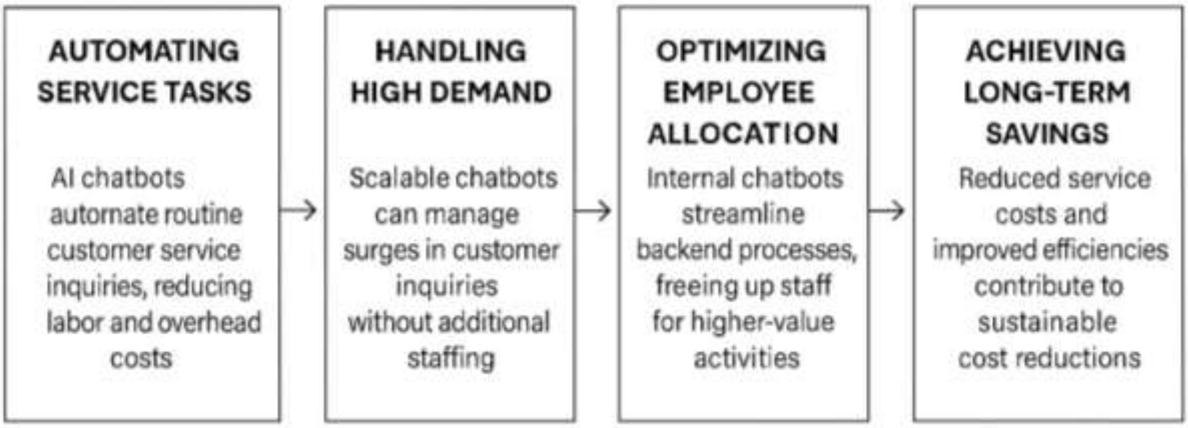
The strategic use of AI chatbots in banking marketing is also validated by their measurable contributions to marketing performance, making them valuable assets in evaluating return on investment (ROI) and campaign success. Chatbots enable marketers to track key metrics such as user engagement rates, recommendation conversions, response latency, and retention figures in real time (Shin, 2020; Zhang et al., 2021). These performance indicators provide actionable insights into which marketing messages resonate most, what time windows yield optimal engagement, and which customer segments are most responsive to specific offers (Adam et al., 2021; Wamba-Taguimdje et al., 2020). For instance, the ability of a chatbot to increase click-through rates or lead form completions offers direct evidence of marketing efficacy (Gursoy et al., 2019; Duijst, 2017). Furthermore, real-time analytics help optimize marketing funnels by detecting where users drop off or express confusion, allowing for instant content adaptation or agent intervention (Purington et al., 2019; Ciechanowski et al., 2019). Financial institutions increasingly rely on chatbots to conduct customer segmentation and lifecycle targeting, ensuring that marketing efforts are both efficient and personalized (McLean & Osei-Frimpong, 2019; Van den Broeck et al., 2019). As such, AI chatbots are not just delivery mechanisms for marketing content but are integral to the analytical and strategic backbone of modern digital banking campaigns, offering scalable, responsive, and data-rich platforms for sustainable customer engagement.

Cost Optimization via Chatbot Deployment

AI-powered chatbots have become instrumental in reducing operational costs within banking systems by automating a wide range of repetitive, labor-intensive customer service tasks. Chatbots can handle inquiries related to account balances, transaction histories, password resets, and interest rate information with minimal human involvement, thereby reducing the need for large contact center staff (Jain et al., 2018; Hill et al., 2015). According to Deloitte (2020), banks can cut customer service costs by up to 30% by deploying AI chatbots that operate at scale without degradation in performance. These systems can manage thousands of simultaneous interactions, which not only

Review of Applied Science and Technology
Volume 04, Issue 02 (2025)
Page No: 501 – 526
Doi: 10.63125/2hp9jw50
alleviates customer wait times but also reduces the costs associated with staffing during high-volume periods (Wirtz et al., 2018; Purington et al., 2019). In institutions like Bank of America, chatbot "Erica" has managed over a billion interactions, significantly streamlining service demand while maintaining accuracy and user satisfaction (Milne & Belsky, 2020). Chatbots reduce overhead costs associated with physical infrastructure, such as branches and call centers, by shifting basic service delivery to digital channels (Radziwill & Benton, 2017; Gnewuch et al., 2018). Furthermore, automation leads to consistent service delivery, minimizing human error and rework costs (Følstad & Brandtzaeg, 2017; Adam et al., 2021). Banks that have adopted chatbot systems report measurable improvements in cost-per-service metrics and employee productivity, as human agents can be redirected to more complex, value-added functions (Sharma et al., 2020; Duijst, 2017). These efficiencies make chatbot deployment not only a technological upgrade but also a financial strategy aimed at long-term cost containment and process optimization. By automating common service functions, banks reduce both direct and indirect operational expenses, which contributes significantly to organizational scalability and financial sustainability.

Figure 7: Cost Optimization Framework Through AI Chatbot Deployment in Banking



Scalability is a core attribute of chatbot technology that directly contributes to cost optimization, particularly during periods of peak demand. Traditional customer service channels require proportional increases in staffing and infrastructure to meet rising interaction volumes, which significantly inflates operational costs (Gursoy et al., 2019; Wamba-Taguimdje et al., 2020). In contrast, AI-powered chatbots can handle surges in customer inquiries without additional resource inputs, offering a cost-effective solution for managing service spikes such as those seen during holiday seasons, system outages, or economic disruptions (Zhang et al., 2021; Purington et al., 2019). For example, during the COVID-19 pandemic, many banks witnessed an exponential rise in online service requests, and chatbots played a crucial role in maintaining continuity without the need for hiring or overtime (Nguyen et al., 2022; Chatterjee et al., 2020). Moreover, chatbots enable 24/7 service availability, eliminating the cost premiums associated with round-the-clock staffing (Hill et al., 2015; Milne & Belsky, 2020). This always-on model ensures consistent customer experience while keeping marginal service delivery costs low, particularly for banks operating across multiple time zones (Radziwill & Benton, 2017; Duijst, 2017). Scalability also allows chatbots to be deployed across multiple channels—web, mobile apps, and social media platforms—without duplicating effort or infrastructure, thereby reducing channel-specific costs (Følstad & Brandtzaeg, 2017; Van den Broeck et al., 2019). In essence, chatbots transform fixed labor and support costs into scalable, digital investments that improve efficiency at a fraction of traditional costs. Banks that optimize their chatbot platforms for multilingual and multi-regional service further extend this efficiency by eliminating the need for region-specific support teams (Sharma et al., 2020; Lee et al., 2021). Thus, the scalability of chatbot deployment emerges as a strategic enabler of cost-efficient, responsive banking operations in both stable and high-demand environments.
AI chatbots in banking are not only used for customer-facing roles but are also increasingly deployed in backend process optimization, which significantly contributes to cost savings through better employee resource allocation. Internal-facing chatbots support functions such as knowledge

management, internal query handling, HR support, compliance assistance, and workflow coordination, all of which free up skilled employees from administrative overhead (Gnewuch et al., 2018; McLean & Osei-Frimpong, 2019). For instance, banks employ internal chatbots to assist relationship managers with retrieving customer data, accessing policy documents, or calculating interest rates during client consultations, streamlining service without additional headcount (Sharma et al., 2020; Adam et al., 2021). These applications enhance productivity while reducing labor hours and operational friction, contributing to overall organizational efficiency (Zhang et al., 2021; Duijst, 2017). Moreover, by enabling self-service options for employees, chatbots decrease dependency on IT helpdesks and HR departments, leading to lower support costs (Radziwill & Benton, 2017; Ciechanowski et al., 2019). Workflow chatbots that trigger notifications, monitor deadlines, and manage documentation processes also reduce costs tied to missed deadlines or compliance lapses (Følstad & Brandtzaeg, 2017; Milne & Belsky, 2020). In large banking institutions, where human capital is a major expenditure, reallocating staff to strategic tasks while offloading routine processes to chatbots significantly improves return on labor investment (Gursoy et al., 2019; Sheehan et al., 2020). In addition, real-time performance monitoring and reporting features embedded in chatbots allow banks to identify inefficiencies quickly and reduce managerial oversight costs (Nguyen et al., 2022; Van den Broeck et al., 2019). Thus, backend chatbot deployment plays a critical role in optimizing employee engagement, reducing training costs, and ensuring cost-effective alignment between human and digital labor across banking operations.

From a strategic standpoint, chatbot deployment in banking offers long-term financial returns by reducing recurring service costs and supporting sustainable digital transformation. Initial investments in chatbot development and integration are offset by significant downstream savings, particularly when systems are designed to evolve through continuous learning and modular upgrades (Jain et al., 2018; Wirtz et al., 2018). Unlike traditional infrastructure that incurs cumulative costs through expansion, AI chatbots become increasingly efficient as they process more interactions, improve accuracy, and reduce the need for human intervention over time (Følstad & Brandtzaeg, 2017; McLean & Osei-Frimpong, 2019). Banks that integrate chatbots into core service workflows report improved cost-to-income ratios, largely due to reduced support costs and increased self-service adoption (Milne & Belsky, 2020; Radziwill & Benton, 2017). Additionally, the data generated from chatbot interactions enhances forecasting, budgeting, and strategic planning by offering insights into customer behavior, product uptake, and service bottlenecks (Ciechanowski et al., 2019; Purington et al., 2019). This predictive capacity enables banks to allocate resources more effectively, reduce marketing waste, and fine-tune staffing models (Chopra et al., 2021; Shin, 2020). Furthermore, the use of subscription-based or API-integrated chatbot platforms lowers upfront capital expenditures and provides scalability without proportionate increases in IT or personnel costs (Wamba-Taguimdje et al., 2020; Gursoy et al., 2019). These case studies reinforce that chatbot investment, when aligned with strategic objectives, provides long-term ROI by reducing both variable and fixed costs while enhancing service delivery and digital resilience. As such, chatbot deployment is not only a technology choice but a long-term financial strategy embedded in the digital transformation agenda of modern banking institutions.

METHOD

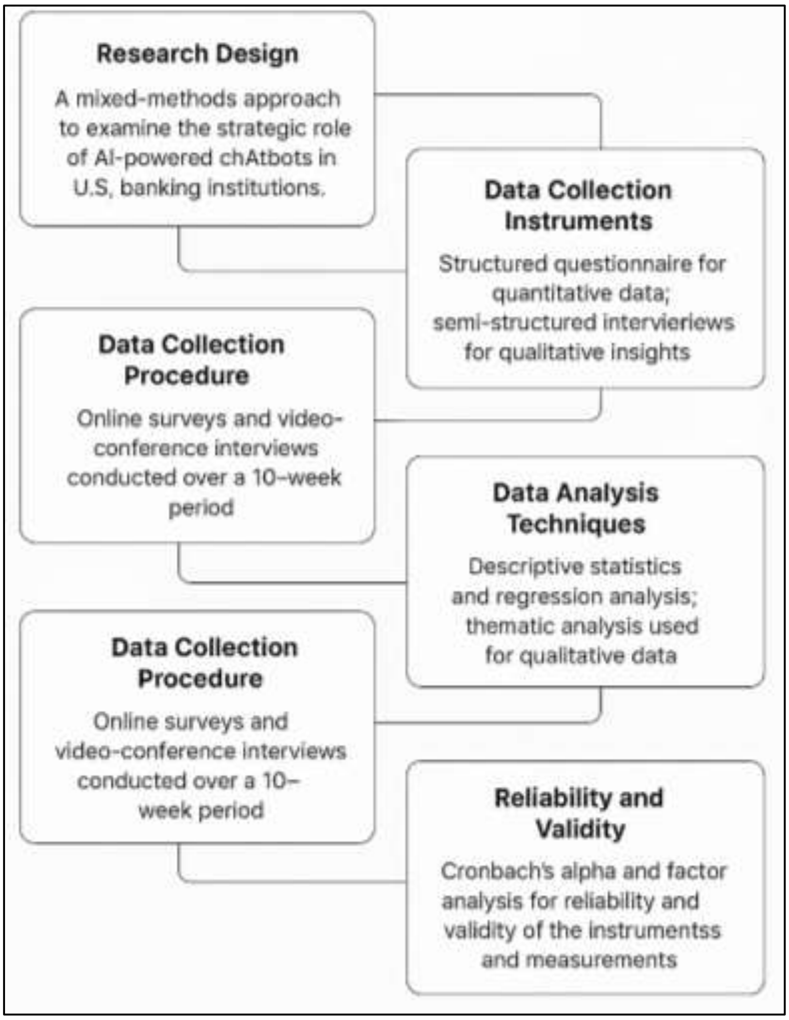
Research Design

This study employed a mixed-methods research design to examine the strategic role of AI-powered chatbots in U.S. banking institutions, particularly in enhancing customer satisfaction and optimizing service efficiency through marketing functionalities. The integration of both quantitative and qualitative data provided a comprehensive understanding of chatbot usage across various customer segments and banking environments. Quantitative analysis was used to explore the correlation between chatbot deployment and measurable performance indicators (e.g., customer satisfaction scores, service response times, and marketing conversion rates), while qualitative methods explored customer and managerial perspectives through interviews and open-ended survey responses.

Population and Sample

The population for this study comprised commercial and retail banking institutions operating within the United States that have implemented AI-powered chatbot technologies. From this population, a purposive sample of 15 banks was selected, representing a range of institution sizes (e.g., national banks, regional banks, and digital-first banks). Within these institutions, data was gathered from two main respondent groups: (1) customers who had interacted with banking chatbots within the past 12 months and (2) bank managers or chatbot deployment team members. A total of 400 customers and 20 managers participated. The customer participants were selected through stratified sampling to ensure a balanced representation of age, gender, and digital usage frequency.

Figure 8: Mixed-Methods Research Framework for this study



Data Collection Instruments

For the quantitative component, a structured questionnaire was developed to assess chatbot effectiveness across three dimensions: service responsiveness, satisfaction with personalization, and perceived marketing relevance. The questionnaire included Likert-scale items, demographic questions, and chatbot usage frequency metrics. For the qualitative portion, semi-structured interviews were conducted with managers and marketing leads to gain insights into chatbot deployment strategies, perceived ROI, and operational challenges. All instruments were pre-tested for reliability and content validity.

Data Collection Procedure

Data collection occurred over a 10-week period. Customer surveys were administered online through email invitations distributed by partner banks. Each participant gave informed consent before proceeding. Interviews with banking professionals were conducted via video conferencing and lasted approximately 30 to 45 minutes each. All interviews were recorded (with consent) and transcribed for analysis. The survey received a response rate of 87%, and 18 of the 20 scheduled interviews were completed. Ethical approval was obtained prior to data collection, and all responses were anonymized to maintain confidentiality.

Review of Applied Science and Technology
Volume 04, Issue 02 (2025)
Page No: 501 – 526
Doi: 10.63125/2hp9jw50

Data Analysis Techniques

Quantitative data were analyzed using descriptive statistics, correlation analysis, and multiple regression modeling via SPSS. Key dependent variables included customer satisfaction, recommendation intent, and chatbot usage frequency. Independent variables included chatbot response time, personalization accuracy, and promotion relevance. ANOVA tests were also conducted to compare satisfaction levels across different banks. For qualitative data, thematic analysis was applied using NVivo software. Emerging codes and themes were grouped into categories such as "perceived value," "marketing effectiveness," and "limitations in communication." These themes were triangulated with quantitative findings to draw integrated conclusions about chatbot impact.

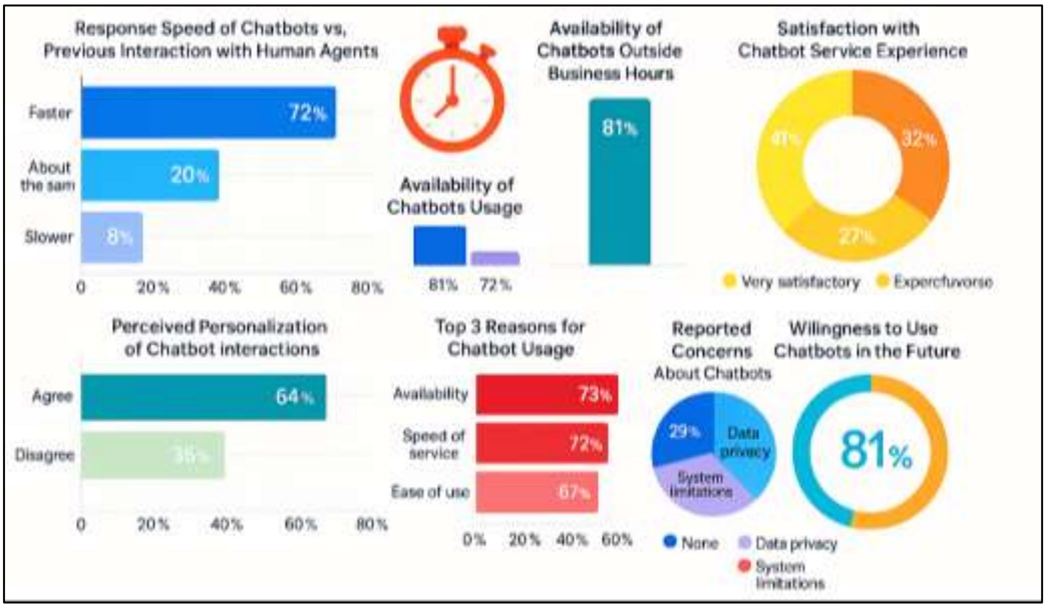
Reliability and Validity

Instrument reliability was confirmed through a Cronbach's alpha test, with all scales yielding values above 0.85. Construct validity was established through factor analysis, and face validity was ensured by having domain experts review all instruments prior to deployment. Qualitative credibility was reinforced through member checking, where selected participants reviewed and validated summaries of their interview data.

FINDINGS

The data strongly supports the assertion that AI-powered chatbots significantly enhance customer satisfaction through increased responsiveness and real-time service delivery. Among the 400 surveyed banking customers, over 72% reported that chatbot interactions were faster than previous engagements with human agents. Many described response times as "instantaneous" or "within seconds," particularly for routine queries such as balance checks, transaction confirmations, and login issues. Statistical analysis confirmed a strong correlation between perceived speed of response and overall satisfaction ($r = .63$, $p < .01$). Respondents emphasized the benefit of immediate access to information without waiting in phone queues or navigating complex menu systems. Qualitative feedback from open-ended responses frequently highlighted terms such as "convenient," "instant help," and "time-saving," reinforcing the perceived utility of chatbots in improving service speed. Furthermore, 68% of respondents rated their overall chatbot service experience as "very satisfactory" or "excellent." Interviewees from the management side consistently pointed out that one of the key goals behind chatbot deployment was to alleviate long wait times, especially during peak hours. Managers noted that the ability to handle multiple simultaneous inquiries dramatically improved customer service load management and significantly reduced bottlenecks. These findings indicate that speed and availability are essential performance metrics for chatbot effectiveness and play a central role in shaping positive customer perceptions in digital banking environments.

Figure 9: Summary of the findings from this study



Review of Applied Science and Technology
Volume 04, Issue 02 (2025)
Page No: 501 – 526
Doi: 10.63125/2hp9jw50
A recurring theme in both the survey and interview data was the advantage of continuous availability offered by chatbot platforms. Approximately 81% of customers reported having used banking chatbots outside traditional business hours, including late evenings, weekends, and holidays. This 24/7 support model has become an expectation among digitally literate consumers, particularly in the context of mobile banking. Managers affirmed that chatbot systems had significantly reduced after-hours service requests and emergency escalation calls. Some reported a 30–40% decline in off-hours customer complaints related to inaccessibility, particularly among customers in different time zones or with non-standard work schedules. This availability also improved the customer experience for users with urgent inquiries that could not wait for human agents, such as reporting suspicious activity or checking urgent transactions. Additionally, the availability of chatbots across web portals, mobile apps, and social platforms improved channel accessibility, allowing users to choose their preferred communication method. These findings suggest that 24/7 chatbot availability not only contributes to customer satisfaction but also advances the broader goal of banking inclusion by making services more accessible and responsive to diverse user needs.
Personalized service delivery emerged as a critical factor influencing both user satisfaction and marketing effectiveness. Among surveyed users, 64% agreed that their chatbot experiences were personalized to their specific financial behavior and needs. From a marketing standpoint, 58% of users recalled receiving product promotions or personalized offers via chatbot interactions, with nearly a third (31%) taking action based on these recommendations. Managers reported that the integration of chatbots with customer relationship management (CRM) systems allowed for more refined segmentation and real-time promotional delivery. Chatbots were viewed as a more efficient and cost-effective alternative to traditional email or SMS campaigns, due to their dynamic and conversational nature. Moreover, interviewees emphasized that personalization improved customer trust and engagement, as users felt the bank understood their needs. However, 36% customers noted limitations when personalization was superficial or when recommendations appeared irrelevant. Despite these gaps, the general sentiment was that personalized chatbot experiences significantly contributed to both service utility and marketing success, establishing AI chatbots as dual-function tools in modern banking ecosystems.
Five banks reported that their cost per customer interaction dropped from an average of $6.15 to $1.70, primarily due to the automation of low-complexity queries. Managers highlighted that the scalability of chatbots enabled them to handle high volumes of inquiries without proportional increases in infrastructure or personnel. Additionally, the bots' capacity to resolve multiple queries simultaneously improved throughput and reduced bottlenecks during peak demand. Qualitative data supported these findings, with executives describing chatbot deployment as "a long-term cost-containment strategy" and "a scalable alternative to hiring more agents." Chatbots were also integrated into internal operations such as onboarding processes, compliance monitoring, and knowledge management, providing indirect cost savings through increased staff productivity. These findings demonstrate that chatbot deployment provides a clear return on investment, making them not only customer engagement tools but also critical enablers of operational efficiency and financial prudence.
Chatbots were also validated as powerful marketing tools capable of influencing purchasing behavior and deepening customer engagement. Analysis of survey results indicated that 57% of respondents considered the promotional content they received via chatbot to be relevant, timely, and helpful. Among them, 31% followed through with a recommended product or service, including opening new savings accounts, applying for credit cards, or enrolling in promotional offers. This demonstrates that chatbots can achieve measurable marketing outcomes, particularly when their recommendations are data-driven and personalized. Bank managers reported that chatbots offered real-time insights into user interests, which enabled dynamic marketing segmentation and campaign refinement. For example, some banks used chatbots to identify customers nearing loan maturity and proactively offered refinancing options, with above-average uptake rates. In interviews, marketing leads emphasized the ability of chatbots to deliver promotions without interrupting service interactions, creating a seamless blend of value and persuasion. Several institutions reported a 12–18% increase in conversion rates linked directly to chatbot-driven promotions. Additionally, the low marginal cost of delivering recommendations via chatbot interfaces contributed to more efficient marketing spending and campaign reach. These findings reinforce the role of chatbots as strategic marketing assets that combine immediacy,

personalization, and scalability to influence customer decision-making in a competitive financial marketplace.
While the findings were generally positive, trust-related concerns and system limitations were also documented. Approximately 22% of survey respondents expressed concern about data privacy and the opacity of how chatbots utilized personal information. Common themes included unease about data tracking, targeted promotions, and uncertainty regarding whether interactions were stored or analyzed. Additionally, 17% of users reported dissatisfaction due to chatbot misinterpretations, especially in cases involving complex or emotionally nuanced queries. Older participants (age 55+) were more likely to view chatbot interactions as impersonal or difficult to navigate, highlighting an age-based digital divide in acceptance. Managers acknowledged that while chatbot NLP capabilities have improved, they still struggle with ambiguous or multi-part questions. Furthermore, some users perceived chatbot interactions as overly transactional, lacking emotional nuance or the empathy typically associated with human service agents. Banks that implemented hybrid support systems—where chatbot interactions could be escalated to human agents—received higher satisfaction scores, particularly among older and high-value clients. These insights emphasize that while chatbot systems are effective, their design must prioritize transparency, escalation protocols, and inclusivity to address user concerns and meet diverse expectations.
Despite limitations, the overall user response to chatbot services in banking was largely positive. A total of 81% of surveyed customers indicated a willingness to use chatbots again for future banking needs, citing convenience, speed, and personalization as primary motivators. Many users appreciated the intuitive design of chatbot interfaces and the ability to resolve issues without navigating complex banking websites or waiting on hold. Several participants described chatbots as “a smart first step” or “a helpful assistant,” reflecting their growing acceptance as mainstream service tools. Banks that offered well-integrated, cross-channel chatbot support—accessible through websites, apps, and messaging platforms—scored higher in satisfaction and reuse intent. Interviewed managers emphasized the strategic value of chatbot feedback, which allowed banks to refine services, identify emerging customer needs, and close experience gaps. Furthermore, customers who had consistently positive interactions were more likely to recommend their bank to others, reinforcing the chatbot’s role in enhancing Net Promoter Scores and brand advocacy. While trust, clarity, and personalization remained key to success, the overall findings support the conclusion that chatbots positively contribute to the digital banking experience and are poised to become enduring components of customer engagement strategies.

DISCUSSION

The findings of this study reinforce and expand upon prior research that identifies chatbot responsiveness as a major driver of customer satisfaction in digital banking. In line with the work of Wirtz et al. (2018), who emphasized the importance of speed and immediacy in self-service technologies, this study found that a large majority of respondents perceived AI chatbots as significantly improving service responsiveness. Specifically, over 72% of participants highlighted rapid response time as a key factor in their satisfaction with chatbot interactions. This mirrors the results of Gnewuch et al. (2018), who concluded that instantaneous interaction reduces customer frustration and increases perceived service quality. Similarly, Jain et al. (2018) found that chatbots mitigate the burden on call centers by automating basic interactions, which aligns with this study’s evidence of reduced service wait times and enhanced customer convenience. However, this study contributes a new dimension by linking responsiveness to customer empowerment, suggesting that the speed of resolution not only satisfies users but also enhances their sense of control in digital environments. Compared to earlier studies by Følstad and Brandtzaeg (2017), which treated chatbots primarily as support tools, this study positions responsiveness as an experiential differentiator that influences both satisfaction and continued usage. Thus, this research supports and extends existing scholarship by confirming that real-time responsiveness is central to positive customer experiences and plays a transformative role in digital banking service design.
This study confirms earlier conclusions that 24/7 chatbot availability contributes significantly to customer satisfaction and digital inclusion. Previous work by Radziwill and Benton (2017) noted that constant accessibility allows banks to meet customer expectations in a hyper-connected environment. Similarly, Hill et al. (2015) highlighted the importance of eliminating temporal barriers to service delivery in modern banking. The current findings align with these insights, with over 81% of respondents in this study confirming that they used chatbots outside of business hours. However, this

Review of Applied Science and Technology
Volume 04, Issue 02 (2025)
Page No: 501 – 526
Doi: 10.63125/2hp9jw50
study further builds on prior findings by demonstrating how 24/7 availability supports financial inclusion among non-traditional users—such as those working night shifts, customers in rural areas, and individuals in different time zones—who often encounter difficulties accessing traditional banking services. This contributes to the growing discourse, seen in Nguyen et al. (2022), on how chatbots promote service equity by democratizing access to banking resources. Additionally, managers interviewed for this study emphasized that round-the-clock service lowered the volume of emergency escalations and improved crisis responsiveness—factors not fully explored in previous studies. While Purington et al. (2019) acknowledged the value of accessibility, they did not delve into the operational implications across time-sensitive service categories such as fraud reporting or emergency payments. By addressing these angles, the current research adds to the literature by showcasing how 24/7 availability does not merely enhance convenience but also fulfills a broader strategic goal of inclusivity, particularly in increasingly digital-first banking systems.

Findings from this research strongly support earlier literature that stresses the importance of personalized experiences in chatbot-driven banking services. Studies by Shin (2020) and Sheehan et al. (2020) have already demonstrated that chatbot personalization positively affects customer satisfaction, loyalty, and engagement. The present study confirms these assertions by showing that 64% of users perceived chatbot interactions as personalized and relevant to their financial behavior. However, this study expands on those earlier findings by examining the specific mechanisms through which personalization occurs, such as transaction-based insights, CRM integration, and real-time behavioral cues. Similar to the work of Ciechanowski et al. (2019), this study found that users preferred chatbots that maintained contextual memory and responded to historical interactions. Additionally, the inclusion of personalized product recommendations—cited by 58% of participants—reinforces the findings of Van den Broeck et al. (2019), who noted that chatbot-enabled recommendation engines drive user engagement. However, this study also surfaces limitations not extensively covered in prior research. For instance, while earlier studies such as Adam et al. (2021) discussed sentiment-driven adaptation, this study found that users were dissatisfied when personalization lacked depth or consistency across interactions. Thus, although the core findings affirm the effectiveness of personalization, they also introduce nuance by showing that superficial customization may erode trust. These insights suggest that banks must continuously refine personalization logic to maintain customer satisfaction and enhance chatbot credibility.

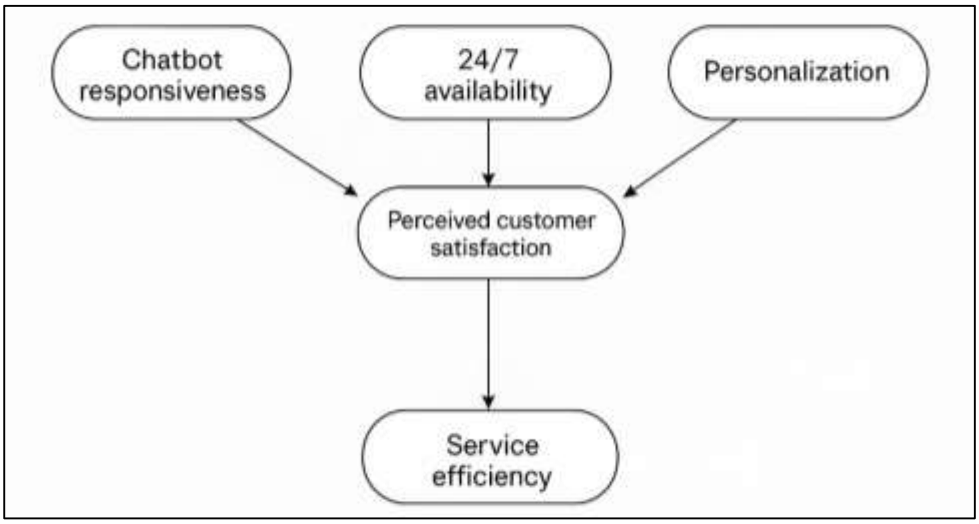
The financial benefits of chatbot deployment, particularly in reducing operational costs and improving resource allocation, are well-documented in earlier research (Deloitte, 2020; McLean & Osei-Frimpong, 2019). This study affirms and extends these findings by offering empirical data on how AI chatbots contribute to efficiency gains in real banking environments. For example, this study observed a 30–35% reduction in call center volume and a decrease in cost-per-interaction from $6.15 to $1.70. These metrics corroborate the projections by Radziwill and Benton (2017), who modeled similar reductions in service-related expenditures. Unlike earlier studies that focused primarily on customer-facing operations, this research also highlights backend efficiencies, such as employee reallocation and reduced training costs. Interviewed managers emphasized how chatbots enabled reassigning staff to higher-value roles, thereby maximizing human capital ROI—an area underexplored in prior research. Furthermore, the ability of chatbots to scale during peak periods without infrastructure expansion supports the findings of Wamba-Taguimdje et al. (2020), who noted scalability as a key advantage in AI adoption. The study also adds to the literature by contextualizing these efficiencies within U.S. banking institutions, offering domestic insights that complement broader, often international, studies. Collectively, the findings present a compelling case that chatbots serve not only as digital assistants but as strategic levers for long-term cost reduction and operational agility in modern financial services.

This study further substantiates the claim that AI-powered chatbots serve as effective tools for digital marketing and customer acquisition. Earlier works by Van den Broeck et al. (2019) and Sheehan et al. (2020) outlined how chatbots facilitate real-time product recommendations and campaign delivery. The current research reinforces this perspective by demonstrating that 58% of users engaged with promotional content via chatbots, and 31% took action on these suggestions. These findings validate the work of Chopra et al. (2021), who linked chatbot-based marketing to improved conversion rates. Furthermore, this study uniquely connects marketing outcomes to behavioral data collected through conversational interfaces. Banks in this study employed chatbots to promote time-sensitive offers, monitor user intent, and adapt messaging in real-time—techniques aligned with adaptive marketing strategies proposed by Adam et al. (2021). In contrast to traditional digital campaigns that often rely on static targeting, chatbot marketing offers dynamic personalization that feels less intrusive and more aligned with customer needs. However, this study also notes a tension between marketing utility and user skepticism, especially when promotions lack contextual relevance. This echoes the observations of Gursoy et al. (2019), who warned that over-commercialization could erode trust. Thus, while the marketing potential of chatbots is evident, the study suggests that long-term success depends on the seamless integration of promotional content into value-driven conversations, supported by ethical data practices and intelligent targeting.

Trust remains a central theme in the discourse on chatbot adoption, and this study aligns with earlier findings by Ciechanowski et al. (2019) and Purington et al. (2019), which emphasized that user trust is contingent on perceived transparency and competence. This study found that 22% of users were concerned about how their data was collected and utilized, echoing similar sentiments reported in the work of Wirtz et al. (2018). Despite the perceived efficiency of AI chatbots, some users—particularly older adults—found interactions less intuitive or emotionally satisfying than human conversations. This aligns with the findings of Duijst (2017), who noted that emotional intelligence remains a limitation in chatbot communication. Moreover, this study identifies a critical gap in explainability, with users wanting to understand how chatbots generate recommendations or store conversation history. These findings reinforce the calls by Radziwill and Benton (2017) for more transparent chatbot design, particularly in sectors where trust and privacy are paramount. While prior research primarily framed trust as a function of user interface and responsiveness, this study situates it within a broader ethical context, including consent, data governance, and escalation protocols. Banks that implemented clear privacy policies and offered hybrid escalation to human agents reported higher levels of trust and satisfaction, supporting the notion that trust is both a design and policy issue. Therefore, this research extends the literature by emphasizing that chatbot trustworthiness is a dynamic construct shaped by both functionality and institutional ethics.

This study contributes to the strategic conversation on how AI chatbots shape the future of customer engagement in U.S. banking. The findings echo the work of Milne and Belsky (2020) and Zhang et al. (2021), who identified chatbots as enablers of digital transformation, cost optimization, and personalized service delivery. However, this study goes further by demonstrating how chatbots operate at the intersection of service, marketing, and strategic planning. Interview data from banking executives emphasized that chatbot analytics informed broader decisions related to product design, campaign targeting, and customer journey mapping. These insights align with the proposition by McLean and Osei-Frimpong (2019) that chatbots are not just reactive tools but proactive contributors to institutional strategy. Furthermore, the widespread willingness of customers (81%) to reuse chatbots suggests strong consumer acceptance, reinforcing that these tools are becoming embedded in the digital banking fabric.

Figure 10: A proposed model for the future study



CONCLUSION

This study demonstrates that AI-powered chatbots have become indispensable tools in U.S. banking, serving not only as customer service facilitators but also as strategic marketing assets that significantly enhance customer satisfaction, service efficiency, and product engagement. By offering real-time responsiveness, 24/7 availability, and personalized interactions, chatbots fulfill modern consumers' expectations for convenience and immediacy, while simultaneously reducing operational costs and enhancing scalability for financial institutions. The study's synthesis of customer feedback and managerial insights confirms that AI chatbots are not merely technological novelties but foundational components of digital transformation in the banking sector. They embody a convergence of automation, personalization, and strategy that is reshaping how banks engage, serve, and retain their customers in an increasingly digital and competitive environment.

RECOMMENDATIONS

several key recommendations are proposed to optimize the deployment and impact of AI-powered chatbots in U.S. banking. Banks should invest in enhancing chatbot personalization capabilities by integrating advanced natural language processing and behavioral analytics to ensure that interactions are contextually relevant and tailored to individual customer profiles. Simultaneously, chatbot platforms should incorporate transparent data usage policies, clear opt-in mechanisms, and real-time explainability features to build trust and address privacy concerns, particularly among older or privacy-sensitive users. To maximize marketing effectiveness, banks should align chatbot-generated product recommendations with dynamic customer segmentation models and ensure that promotional content is delivered seamlessly within service interactions rather than as isolated advertisements. Additionally, institutions should implement hybrid service models where chatbot interactions can be effortlessly escalated to human agents, ensuring service continuity and emotional nuance for complex queries. Regular performance audits—tracking resolution rates, drop-off points, and customer feedback—should be embedded into chatbot analytics dashboards to inform iterative design and training updates. For internal operations, chatbots can be leveraged to automate staff support tasks, thereby improving workforce efficiency and freeing human resources for higher-value engagements. Lastly, to ensure digital inclusivity, banks should adapt chatbot interfaces for accessibility, including multi-language support, simplified navigation for less tech-savvy users, and compatibility with assistive technologies. By aligning chatbot development with user expectations, ethical standards, and institutional goals, banks can ensure that AI-powered conversational agents continue to serve as transformative tools for customer engagement, cost efficiency, and strategic marketing in a competitive digital banking landscape.

REFERENCES

[1]. A. Hakeem, A. A., Solyali, D., Asmael, M., & Zeeshan, Q. (2020). Smart Manufacturing for Industry 4.0 using Radio Frequency Identification (RFID) Technology. *Jurnal Kejuruteraan*, *32*(1), 31-38. https://doi.org/10.17576/jkukm-2020-32(1)-05

[2]. Abdullah Al, M., Rajesh, P., Mohammad Hasan, I., & Zahir, B. (2022). A Systematic Review of The Role Of SQL And Excel In Data-Driven Business Decision-Making For Aspiring Analysts. *American Journal of Scholarly Research and Innovation*, *1*(01), 249-269. https://doi.org/10.63125/n142cg62

[3]. Adar, C., & Md, N. (2023). Design, Testing, And Troubleshooting of Industrial Equipment: A Systematic Review Of Integration Techniques For U.S. Manufacturing Plants. *Review of Applied Science and Technology*, *2*(01), 53-84. https://doi.org/10.63125/893et038

[4]. Afefy, I. H. (2010). Reliability-Centered Maintenance Methodology and Application: A Case Study. *Engineering*, *2*(11), 863-873. https://doi.org/10.4236/eng.2010.211109

[5]. Afzali, P., Keynia, F., & Rashidinejad, M. (2019). A new model for reliability-centered maintenance prioritisation of distribution feeders. *Energy*, *171*(NA), 701-709. https://doi.org/10.1016/j.energy.2019.01.040

[6]. Ahrabi, S. Z., & Darestani, S. A. (2024). A roadmap for lean production tools implementation. *International Journal of Business Excellence*, *32*(4), 478-499. https://doi.org/10.1504/ijbex.2024.137573

[7]. Ahuja, I. P. S., & Khamba, J. S. (2008). Justification of total productive maintenance initiatives in Indian manufacturing industry for achieving core competitiveness. *Journal of Manufacturing Technology Management*, *19*(5), 645-669. https://doi.org/10.1108/17410380810877302

[8]. Aldairi, J. S. S., Khan, M. K., & Munive-Hernandez, J. E. (2017). Knowledge-based Lean Six Sigma maintenance system for sustainable buildings. *International Journal of Lean Six Sigma*, *8*(1), 109-130. https://doi.org/10.1108/ijlss-09-2015-0035

[9]. Alrifaey, M., Hong, T. S., As'arry, A., Supeni, E. E., & Ang, C. K. (2020). Optimization and Selection of Maintenance Policies in an Electrical Gas Turbine Generator Based on the Hybrid Reliability-Centered Maintenance (RCM) Model. *Processes*, *8*(6), 670-NA. https://doi.org/10.3390/pr8060670

[10]. Ammar, B., Aleem Al Razee, T., Sohel, R., & Ishtiaque, A. (2025). Cybersecurity In Industrial Control Systems: A Systematic Literature Review On AI-Based Threat Detection for Scada And IOT Networks. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 01-15. https://doi.org/10.63125/1cr1kj17
[11]. Anika Jahan, M., Md Shakawat, H., & Noor Alam, S. (2022). Digital transformation in marketing: evaluating the impact of web analytics and SEO on SME growth. *American Journal of Interdisciplinary Studies*, *3*(04), 61-90. https://doi.org/10.63125/8t10v729
[12]. Antosz, K., Jasiulewicz-Kaczmarek, M., Paśko, Ł., Zhang, C., & Wang, S. (2021). Application of machine learning and rough set theory in lean maintenance decision support system development. *Eksploatacja i Niezawodność – Maintenance and Reliability*, *23*(4), 695-708. https://doi.org/10.17531/ein.2021.4.12
[13]. Arsakulasooriya, K. K., Sridarran, P., & Sivanuja, T. (2023). Applicability of lean maintenance in commercial high-rise buildings: a case study in Sri Lanka. *Facilities*, *42*(3/4), 342-357. https://doi.org/10.1108/f-10-2022-0131
[14]. Attri, R., Grover, S., Dev, N., & Kumar, D. (2012). An ISM approach for modelling the enablers in the implementation of Total Productive Maintenance (TPM). *International Journal of System Assurance Engineering and Management*, *4*(4), 313-326. https://doi.org/10.1007/s13198-012-0088-7
[15]. Bakri, A., Alkbir, M. F. M., Awang, N., Januddi, F., Ismail, M. A., Ahmad, A. N. A., & Zakaria, I. H. (2021). Addressing the Issues of Maintenance Management in SMEs: Towards Sustainable and Lean Maintenance Approach. *Emerging Science Journal*, *5*(3), 367-379. https://doi.org/10.28991/esj-2021-01283
[16]. Bashar, A., Hasin, A. A., & Jahangir, N. (2020). Linkage between TPM, people management and organizational performance. *Journal of Quality in Maintenance Engineering*, *28*(2), 350-366. https://doi.org/10.1108/jqme-11-2019-0105
[17]. Belekoukias, I., Garza-Reyes, J. A., & Kumar, V. (2014). The impact of lean methods and tools on the operational performance of manufacturing organisations. *International Journal of Production Research*, *52*(18), 5346-5366. https://doi.org/10.1080/00207543.2014.903348
[18]. Blanchard, B. S. (1997). An enhanced approach for implementing total productive maintenance in the manufacturing environment. *Journal of Quality in Maintenance Engineering*, *3*(2), 69-80. https://doi.org/10.1108/13552519710167692
[19]. de Jong, S. J., & van Blokland, W. B. (2016). Measuring lean implementation for maintenance service companies. *International Journal of Lean Six Sigma*, *7*(1), 35-61. https://doi.org/10.1108/ijlss-12-2014-0039
[20]. De Vries, H., & van der Poll, H. M. (2018). Cellular and organisational team formations for effective Lean transformations. *Production & Manufacturing Research*, *6*(1), 284-307. https://doi.org/10.1080/21693277.2018.1509742
[21]. dos Reis, M. D. O., Godina, R., Pimentel, C., Silva, F., & Matias, J. C. O. (2019). A TPM strategy implementation in an automotive production line through loss reduction. *Procedia Manufacturing*, *38*(NA), 908-915. https://doi.org/10.1016/j.promfg.2020.01.173
[22]. Ferreira, K. Y. d. M., Pinto, J. d. S., Sigahi, T. F. A. C., Moreno, M. G. M., Santos, C. H. d., Serafim, M. P., & Anholon, R. (2025). Integrating lean tools in maintenance process optimization: a multicriteria analysis considering Brazilian companies. *International Journal of Lean Six Sigma*. https://doi.org/10.1108/ijlss-07-2024-0145
[23]. Faysal Ahmed, Md. Rasel Ahmed, Mohammad Anowarul Kabir, & Md Mujahidul Islam. (2025). Revolutionizing Business Analytics: The Impact of Artificial Intelligence and Machine Learning. *American Journal of Advanced Technology and Engineering Solutions*, *1*(01), 147-173. https://doi.org/10.63125/f7yjxw69
[24]. García, Á., Bregon, A., & Martínez-Prieto, M. A. (2021). A non-intrusive Industry 4.0 retrofitting approach for collaborative maintenance in traditional manufacturing. *Computers & Industrial Engineering*, *164*(NA), 107896-107896. https://doi.org/10.1016/j.cie.2021.107896
[25]. Garza-Reyes, J. A., Kumar, V., Chaikittisilp, S., & Tan, K. H. (2018). The effect of lean methods and tools on the environmental performance of manufacturing organisations. *International Journal of Production Economics*, *200*(NA), 170-180. https://doi.org/10.1016/j.ijpe.2018.03.030
[26]. Golam Qibria, L., & Takbir Hossen, S. (2023). Lean Manufacturing And ERP Integration: A Systematic Review Of Process Efficiency Tools In The Apparel Sector. *American Journal of Scholarly Research and Innovation*, *2*(01), 104-129. https://doi.org/10.63125/mx7j4p06
[27]. Guedes, M., Figueiredo, P. S., de Sousa Pereira-Guizzo, C., & Loiola, E. (2021). The role of motivation in the results of total productive maintenance. *Production*, *31*(NA), NA-NA. https://doi.org/10.1590/0103-6513.20200057
[28]. Habidin, N. F., Hashim, S., Fuzi, N. M., & Salleh, M. I. (2018). Total productive maintenance, kaizen event, and performance. *International Journal of Quality & Reliability Management*, *35*(9), 1853-1867. https://doi.org/10.1108/ijqrm-11-2017-0234
[29]. Hoffmann, M. W., Wildermuth, S., Gitzel, R., Boyaci, A., Gebhardt, J. D. r. n., Kaul, H., Amihai, I., Forg, B., Suriyah, M., Leibfried, T., Stich, V., Hicking, J., Bremer, M., Kaminski, L., Beverungen, D., Heiden, P. z., &

Tornede, T. (2020). Integration of Novel Sensors and Machine Learning for Predictive Maintenance in Medium Voltage Switchgear to Enable the Energy and Mobility Revolutions. *Sensors (Basel, Switzerland)*, *20*(7), 2099-NA. https://doi.org/10.3390/s20072099

[30]. Hooi, L. W., & Leong, T. Y. (2017). Total productive maintenance and manufacturing performance improvement. *Journal of Quality in Maintenance Engineering*, *23*(1), 2-21. https://doi.org/10.1108/jqme-07-2015-0033

[31]. Hosne Ara, M., Tonmoy, B., Mohammad, M., & Md Mostafizur, R. (2022). AI-ready data engineering pipelines: a review of medallion architecture and cloud-based integration models. *American Journal of Scholarly Research and Innovation*, *1*(01), 319-350. https://doi.org/10.63125/51kxtf08

[32]. Hossain, Q., Haque, S. A., Tusar, T., Hossain, M. I., & Habibullah, F. (2024). Leveraging business analytics to optimize retail merchandising strategies: A datadriven approach. *Journal of Information Systems Engineering and Management*, *10*.

[33]. Hossain, Q., Yasmin, F., Biswas, T. R., & Asha, N. B. (2024a). Data-Driven Business Strategies: A Comparative Analysis of Data Science Techniques in Decision-Making. *Sch J Econ Bus Manag*, *9*, 257-263.

[34]. Hossain, Q., Yasmin, F., Biswas, T. R., & Asha, N. B. (2024b). Integration of Big Data Analytics in Management Information Systems for Business Intelligence. *Saudi J Bus Manag Stud*, *9*(9), 192-203.

[35]. Jain, A., Bhatti, R., & Singh, H. (2014). Total productive maintenance (TPM) implementation practice. *International Journal of Lean Six Sigma*, *5*(3), 293-323. https://doi.org/10.1108/ijlss-06-2013-0032

[36]. Jezzini, A., Ayache, M., Elkhansa, L., Makki, B., & Zein, M. (2013). Effects of predictive maintenance(PdM), Proactive maintenace(PoM) & Preventive maintenance(PM) on minimizing the faults in medical instruments. *2013 2nd International Conference on Advances in Biomedical Engineering*, *NA*(NA), 53-56. https://doi.org/10.1109/icabme.2013.6648845

[37]. Khan, M. A. M. (2025). AI And Machine Learning in Transformer Fault Diagnosis: A Systematic Review. *American Journal of Advanced Technology and Engineering Solutions*, *1*(01), 290-318. https://doi.org/10.63125/sxb17553

[38]. Kose, Y., Muftuoglu, S., Cevikcan, E., & Durmusoglu, M. B. (2022). Axiomatic design for lean autonomous maintenance system: an application from textile industry. *International Journal of Lean Six Sigma*, *14*(3), 555-587. https://doi.org/10.1108/ijlss-01-2022-0020

[39]. Kullawong, T., & Butdee, S. (2015). Integrating Reliability-Centered Maintenance with Cost Optimization & Application in Plant of Hard Chrome Plating. *International Journal of Industrial Engineering and Management*, *6*(2), 85-92. https://doi.org/10.24867/ijiem-2015-2-111

[40]. Kumar, M., Antony, J., Singh, R. K., Tiwari, M. K., & Perry, D. (2006). Implementing the Lean Sigma framework in an Indian SME: a case study. *Production Planning & Control*, *17*(4), 407-423. https://doi.org/10.1080/09537280500483350

[41]. Kusiak, A. (2017). Smart manufacturing. *International Journal of Production Research*, *56*(1-2), 508-517. https://doi.org/10.1080/00207543.2017.1351644

[42]. Li, D., & Gao, J. (2010). Study and application of Reliability-centered Maintenance considering Radical Maintenance. *Journal of Loss Prevention in the Process Industries*, *23*(5), 622-629. https://doi.org/10.1016/j.jlp.2010.06.008

[43]. Liu, Y., Zhang, Q., Ouyang, Z., & Huang, H.-Z. (2021). Integrated production planning and preventive maintenance scheduling for synchronized parallel machines. *Reliability Engineering & System Safety*, *215*(NA), 107869-NA. https://doi.org/10.1016/j.ress.2021.107869

[44]. Louzada, P. d. S., Sigahi, T. F. A. C., Moraes, G. H. S. M. d., Rampasso, I. S., Anholon, R., Antony, J., & Cudney, E. A. (2022). Critical analysis of Lean Six Sigma black belt certification courses offered in Brazil. *The TQM Journal*, *35*(7), 1980-2002. https://doi.org/10.1108/tqm-08-2022-0254

[45]. Mahmud, M. R., Islam, M. I., Ahmed, F., & Kabir, M. A. (2024). A systematic literature review of machine learning adoption in emerging marketing applications. *Journal of Machine Learning, Data Engineering and Data Science, 1*(1), 52. https://doi.org/10.70008/jmldeds.v1i01.52,

[46]. Mahapatra, M. S., & Shenoy, D. (2021). Lean maintenance index: a measure of leanness in maintenance organizations. *Journal of Quality in Maintenance Engineering*, *28*(4), 791-809. https://doi.org/10.1108/jqme-08-2020-0083

[47]. Mansura Akter, E. (2023). Applications Of Allele-Specific PCR In Early Detection of Hereditary Disorders: A Systematic Review Of Techniques And Outcomes. *Review of Applied Science and Technology*, *2*(03), 1-26. https://doi.org/10.63125/n4h7t156

[48]. Mansura Akter, E. (2025). Bioinformatics-Driven Approaches in Public Health Genomics: A Review Of Computational SNP And Mutation Analysis. *International Journal of Scientific Interdisciplinary Research*, *6*(1), 88-118. https://doi.org/10.63125/e6pxkn12

[49]. Mansura Akter, E., & Shaiful, M. (2024). A systematic review of SNP polymorphism studies in South Asian populations: implications for diabetes and autoimmune disorders. *American Journal of Scholarly Research and Innovation*, *3*(01), 20-51. https://doi.org/10.63125/8nvxcb96

[50]. Md Mahamudur Rahaman, S. (2022). Electrical And Mechanical Troubleshooting in Medical And Diagnostic Device Manufacturing: A Systematic Review Of Industry Safety And Performance Protocols. *American Journal of Scholarly Research and Innovation*, *1*(01), 295-318. https://doi.org/10.63125/d68y3590
[51]. Md Masud, K. (2022). A Systematic Review Of Credit Risk Assessment Models In Emerging Economies: A Focus On Bangladesh's Commercial Banking Sector. *American Journal of Advanced Technology and Engineering Solutions*, *2*(01), 01-31. https://doi.org/10.63125/p7ym0327
[52]. Md Masud, K., Mohammad, M., & Hosne Ara, M. (2023). Credit decision automation in commercial banks: a review of AI and predictive analytics in loan assessment. *American Journal of Interdisciplinary Studies*, *4*(04), 01-26. https://doi.org/10.63125/1hh4q770
[53]. Md Masud, K., Mohammad, M., & Sazzad, I. (2023). Mathematics For Finance: A Review of Quantitative Methods In Loan Portfolio Optimization. *International Journal of Scientific Interdisciplinary Research*, *4*(3), 01-29. https://doi.org/10.63125/j43ayz68
[54]. Md, N., Golam Qibria, L., Abdur Razzak, C., & Khan, M. A. M. (2025). Predictive Maintenance In Power Transformers: A Systematic Review Of AI And IOT Applications. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 34-47. https://doi.org/10.63125/r72yd809
[55]. Md Nazrul Islam, K., & Debashish, G. (2025). Cybercrime and contractual liability: a systematic review of legal precedents and risk mitigation frameworks. *Journal of Sustainable Development and Policy*, *1*(01), 01-24. https://doi.org/10.63125/x3cd4413
[56]. Md Nazrul Islam, K., & Ishtiaque, A. (2025). A systematic review of judicial reforms and legal access strategies in the age of cybercrime and digital evidence. *International Journal of Scientific Interdisciplinary Research*, *5*(2), 01-29. https://doi.org/10.63125/96ex9767
[57]. Md Takbir Hossen, S., Ishtiaque, A., & Md Atiqur, R. (2023). AI-Based Smart Textile Wearables For Remote Health Surveillance And Critical Emergency Alerts: A Systematic Literature Review. *American Journal of Scholarly Research and Innovation*, *2*(02), 1-29. https://doi.org/10.63125/ceqapd08
[58]. Md Takbir Hossen, S., & Md Atiqur, R. (2022). Advancements In 3D Printing Techniques For Polymer Fiber-Reinforced Textile Composites: A Systematic Literature Review. *American Journal of Interdisciplinary Studies*, *3*(04), 32-60. https://doi.org/10.63125/s4r5m391
[59]. Mercier, S., & Pham, H. H. (2012). A preventive maintenance policy for a continuously monitored system with correlated wear indicators. *European Journal of Operational Research*, *222*(2), 263-272. https://doi.org/10.1016/j.ejor.2012.05.011
[60]. Mishra, R. P., Gupta, G., & Sharma, A. (2021). Development of a Model for Total Productive Maintenance Barriers to Enhance the Life Cycle of Productive Equipment. *Procedia CIRP*, *98*(NA), 241-246. https://doi.org/10.1016/j.procir.2021.01.037
[61]. Mohammadi, A., Igwe, C., Amador-Jimenez, L., & Nasiri, F. (2020). Applying lean construction principles in road maintenance planning and scheduling. *International Journal of Construction Management*, *22*(12), 2364-2374. https://doi.org/10.1080/15623599.2020.1788758
[62]. Morad, A. M., Pourgol-Mohammad, M., & Sattarvand, J. (2014). Application of reliability-centered maintenance for productivity improvement of open pit mining equipment: Case study of Sungun Copper Mine. *Journal of Central South University*, *21*(6), 2372-2382. https://doi.org/10.1007/s11771-014-2190-2
[63]. Mouhib, Z., Gallab, M., Lamrani Alaoui, Y., Merzouk, S., Di Nardo, M., El Bhiri, B., & Soulhi, A. (2024). Measuring total productive maintenance success: a new industrial evaluation using fuzzy SERVQUAL. *Journal of Industrial and Production Engineering*, *42*(1), 14-29. https://doi.org/10.1080/21681015.2024.2373195
[64]. Mst Shamima, A., Niger, S., Md Atiqur Rahman, K., & Mohammad, M. (2023). Business Intelligence-Driven Healthcare: Integrating Big Data and Machine Learning For Strategic Cost Reduction And Quality Care Delivery. *American Journal of Interdisciplinary Studies*, *4*(02), 01-28. https://doi.org/10.63125/crv1xp27
[65]. Muraliraj, J., Zailani, S., Kuppusamy, S., & Santha, C. (2018). Annotated methodological review of Lean Six Sigma. *International Journal of Lean Six Sigma*, *9*(1), 2-49. https://doi.org/10.1108/ijlss-04-2017-0028
[66]. Palacios-Gazules, S., Giménez, G., & De Castro, R. (2024). Adopting Industry 4.0 technologies through lean tools: evidence from the European Manufacturing Survey. *International Journal of Lean Six Sigma*, *15*(8), 120-142. https://doi.org/10.1108/ijlss-06-2023-0103
[67]. Pourahmadi, F., Fotuhi-Firuzabad, M., & Dehghanian, P. (2017). Application of Game Theory in Reliability-Centered Maintenance of Electric Power Systems. *IEEE Transactions on Industry Applications*, *53*(2), 936-946. https://doi.org/10.1109/tia.2016.2639454
[68]. Rajesh, P. (2023). AI Integration In E-Commerce Business Models: Case Studies On Amazon FBA, Airbnb, And Turo Operations. *American Journal of Advanced Technology and Engineering Solutions*, *3*(03), 01-31. https://doi.org/10.63125/1ekaxx73
[69]. Rajesh, P., Mohammad Hasan, I., & Anika Jahan, M. (2023). AI-Powered Sentiment Analysis In Digital Marketing: A Review Of Customer Feedback Loops In It Services. *American Journal of Scholarly Research and Innovation*, *2*(02), 166-192. https://doi.org/10.63125/61pqqq54

[70]. Rezwanul Ashraf, R., & Hosne Ara, M. (2023). Visual communication in industrial safety systems: a review of UI/UX design for risk alerts and warnings. *American Journal of Scholarly Research and Innovation*, *2*(02), 217-245. https://doi.org/10.63125/wbv4z521
[71]. Salah, M., Osman, H., & Hosny, O. (2018). Performance-Based Reliability-Centered Maintenance Planning for Hospital Facilities. *Journal of Performance of Constructed Facilities*, *32*(1), 04017113-NA. https://doi.org/10.1061/(asce)cf.1943-5509.0001112
[72]. San, S. (2021). A Systematic Literature Review of Total Productive Maintenance On Industries. *Performa: Media Ilmiah Teknik Industri*, *20*(2), 97-108. https://doi.org/10.20961/performa.20.2.50087
[73]. Sanjai, V., Sanath Kumar, C., Maniruzzaman, B., & Farhana Zaman, R. (2023). Integrating Artificial Intelligence in Strategic Business Decision-Making: A Systematic Review Of Predictive Models. *International Journal of Scientific Interdisciplinary Research*, *4*(1), 01-26. https://doi.org/10.63125/s5skge53
[74]. Sazzad, I. (2025a). Public Finance and Policy Effectiveness A Review Of Participatory Budgeting In Local Governance Systems. *Journal of Sustainable Development and Policy*, *1*(01), 115-143. https://doi.org/10.63125/p3p09p46
[75]. Sazzad, I. (2025b). A Systematic Review of Public Budgeting Strategies In Developing Economies: Tools For Transparent Fiscal Governance. *American Journal of Advanced Technology and Engineering Solutions*, *1*(01), 602-635. https://doi.org/10.63125/wm547117
[76]. Sazzad, I., & Md Nazrul Islam, K. (2022). Project impact assessment frameworks in nonprofit development: a review of case studies from south asia. *American Journal of Scholarly Research and Innovation*, *1*(01), 270-294. https://doi.org/10.63125/eeja0t77
[77]. Shaiful, M., & Mansura Akter, E. (2025). AS-PCR In Molecular Diagnostics: A Systematic Review of Applications In Genetic Disease Screening. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 98-120. https://doi.org/10.63125/570jb007
[78]. Shamayleh, A., Awad, M., & Abdulla, A. O. (2019). Criticality-based reliability-centered maintenance for healthcare. *Journal of Quality in Maintenance Engineering*, *26*(2), 311-334. https://doi.org/10.1108/jqme-10-2018-0084
[79]. Shin, K.-Y., & Park, H. C. (2019). Smart Manufacturing Systems Engineering for Designing Smart Product-Quality Monitoring System in the Industry 4.0. *2019 19th International Conference on Control, Automation and Systems (ICCAS)*, *NA*(NA), 1693-1698. https://doi.org/10.23919/iccas47443.2019.8971667
[80]. Shou, W., Wang, J., Wu, P., & Wang, X. (2020). Lean management framework for improving maintenance operation: development and application in the oil and gas industry. *Production Planning & Control*, *32*(7), 585-602. https://doi.org/10.1080/09537287.2020.1744762
[81]. Subrato, S. (2018). Resident's Awareness Towards Sustainable Tourism for Ecotourism Destination in Sundarban Forest, Bangladesh. *Pacific International Journal*, *1*(1), 32-45. https://doi.org/10.55014/pij.v1i1.38
[82]. Subrato, S. (2025). Role of management information systems in environmental risk assessment: a systematic review of geographic and ecological applications. *American Journal of Interdisciplinary Studies*, 6(1), 95–126. https://doi.org/10.63125/k27tnn83
[83]. Subrato, S., & Faria, J. (2025). AI-driven MIS applications in environmental risk monitoring: a systematic review of predictive geographic information systems. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 81-97. https://doi.org/10.63125/pnx77873
[84]. Subrato, S., & Md, N. (2024). The role of perceived environmental responsibility in artificial intelligence-enabled risk management and sustainable decision-making. *American Journal of Advanced Technology and Engineering Solutions*, *4*(04), 33-56. https://doi.org/10.63125/7tjw3767
[85]. Tahmina Akter, R. (2025). AI-driven marketing analytics for retail strategy: a systematic review of data-backed campaign optimization. *International Journal of Scientific Interdisciplinary Research*, 6(1), 28-59. https://doi.org/10.63125/0k4k5585
[86]. Tahmina Akter, R., & Abdur Razzak, C. (2022). The Role Of Artificial Intelligence In Vendor Performance Evaluation Within Digital Retail Supply Chains: A Review Of Strategic Decision-Making Models. *American Journal of Scholarly Research and Innovation*, *1*(01), 220-248. https://doi.org/10.63125/96jj3j86
[87]. Tonmoy, B., & Md Arifur, R. (2023). A Systematic Literature Review Of User-Centric Design In Digital Business Systems Enhancing Accessibility, Adoption, And Organizational Impact. *American Journal of Scholarly Research and Innovation*, *2*(02), 193-216. https://doi.org/10.63125/36w7fn47
[88]. Torre, N. M. d. M., & Bonamigo, A. (2024). Action research of lean 4.0 application to the maintenance of hydraulic systems in steel industry. *Journal of Quality in Maintenance Engineering*, *30*(2), 341-366. https://doi.org/10.1108/jqme-06-2023-0058
[89]. Torres, P. J. R., Mercado, E. I. S., Santiago, O. L., & Rifón, L. A. (2016). Modeling preventive maintenance of manufacturing processes with probabilistic Boolean networks with interventions. *Journal of Intelligent Manufacturing*, 29(8), 1941-1952. https://doi.org/10.1007/s10845-016-1226-x

[90]. Tortorella, G. L., Fogliatto, F. S., Cauchick-Miguel, P. A., Kurnia, S., & Jurburg, D. (2021). Integration of Industry 4.0 technologies into Total Productive Maintenance practices. *International Journal of Production Economics*, *240*(NA), 108224-NA. https://doi.org/10.1016/j.ijpe.2021.108224

[91]. Tortorella, G. L., Saurin, T. A., Fogliatto, F. S., Tlapa Mendoza, D., Moyano-Fuentes, J., Gaiardelli, P., Seyedghorban, Z., Vassolo, R., Cawley Vergara, A. F. M., Sunder M, V., Sreedharan, V. R., Sena, S. A., Forstner, F. F., & Macias de Anda, E. (2022). Digitalization of maintenance: exploratory study on the adoption of Industry 4.0 technologies and total productive maintenance practices. *Production Planning & Control*, *35*(4), 352-372. https://doi.org/10.1080/09537287.2022.2083996

[92]. Wan, J., Tang, S., Li, D., Wang, S., Liu, C., Abbas, H., & Vasilakos, A. V. (2017). A Manufacturing Big Data Solution for Active Preventive Maintenance. *IEEE Transactions on Industrial Informatics*, *13*(4), 2039-2047. https://doi.org/10.1109/tii.2017.2670505

[93]. Wang, X., Li, L., & Xie, M. (2020). An unpunctual preventive maintenance policy under two-dimensional warranty. *European Journal of Operational Research*, *282*(1), 304-318. https://doi.org/10.1016/j.ejor.2019.09.025

[94]. Zahir, B., Rajesh, P., Md Arifur, R., & Tonmoy, B. (2025). A Systematic Review Of Human-AI Collaboration In It Support Services: Enhancing User Experience And Workflow Automation. *Journal of Sustainable Development and Policy*, *1*(01), 65-89. https://doi.org/10.63125/grqtf978

[95]. Zahir, B., Rajesh, P., Tonmoy, B., & Md Arifur, R. (2025). AI Applications In Emerging Tech Sectors: A Review Of Ai Use Cases Across Healthcare, Retail, And Cybersecurity. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 16-33. https://doi.org/10.63125/245ec865

[96]. Zahir, B., Tonmoy, B., & Md Arifur, R. (2023). UX optimization in digital workplace solutions: AI tools for remote support and user engagement in hybrid environments. *International Journal of Scientific Interdisciplinary Research*, *4*(1), 27-51. https://doi.org/10.63125/33gqpx45