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EXAMINING THE IMPACT OF ARTIFICIAL INTELLIGENCE ON CUSTOMER SATISFACTION IN THE BANKING INDUSTRY

DORCAS ESSUMAN

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DECLARATION

I hereby declare that this research is a result of my own original research and that no part of it has been presented for another degree in this university or any other higher education institute. I further declare that all the sources that I have used or quoted have been indicated and acknowledged by means of complete references.

9-12-2025

DORCAS ESSUMAN **DATE**

(MAPRM24001)

CERTIFICATION

This Dissertation has been prepared and presented under my supervision according to the guidelines for supervision and formatting of Dissertation laid down by the University of Media, Arts and Communication (UniMAC).

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18th December 2025

PRISCILLA TEIKA ODOOM, PhD **DATE**

(SUPERVISOR)

DEDICATION

This research is dedicated to those who believe in the power of change and the continuous improvement of systems for the greater good.

To my family, for your unconditional love, unwavering support, and endless encouragement. Your sacrifices and belief in my dreams have shaped the person I am today. This accomplishment is as much yours as it is mine.

To my mentors and educators, especially Dr. Priscilla Teika Odoom who guided, challenged, and inspired me throughout my academic journey. Your wisdom and dedication to nurturing minds have not only imparted knowledge but also instilled a lifelong love for learning.

And finally, to future researchers and students in this field, may this study serve as a steppingstone for further exploration and contribute to meaningful reforms in public service delivery. Your pursuit of knowledge and improvement has the power to make a significant impact on societies.

This work is a tribute to all of you.

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ABSTRACT

This study examined how artificial intelligence (AI) powered customer service tools shape customer satisfaction within Ghana's banking sector, using OmniBSIC Bank Ghana Limited as the focal institution. It drew on Expectation Confirmation Theory to explain how customers compare prior expectations with the performance of AI tools such as chatbots, fraud alerts and automated assistants and how these evaluations influence satisfaction, and the aim of the study was to examine how AI powered customer service tools shape customer satisfaction at OmniBSIC Bank. The study adopted a quantitative cross sectional survey design and targeted an estimated accessible population of 1,000 OmniBSIC customers who had used AI powered service tools, from which 286 respondents were selected through purposive and convenience sampling; data were collected with a structured questionnaire and analysed using descriptive statistics, correlation, regression and structural equation modelling. The study revealed that most respondents used multiple AI tools, especially fraud alerts and chatbots, rated response speed, interface quality and security features favourably and reported high overall satisfaction, while structural equation modelling showed a strong positive effect of AI feature performance on satisfaction through customers' evaluations of AI tool quality; the study recommended that OmniBSIC Bank enhance personalisation, strengthen communication on AI security and maintain seamless access to human support to sustain these satisfaction gains.

Contents

LIST OF TABLES

CHAPTER ONE

INTRODUCTION

1.0 CHAPTER OVERVIEW

This chapter lays the foundational groundwork for the entire study, providing a comprehensive overview of its scope and objectives. It begins by setting the stage for the detailed examination of Artificial Intelligence (AI) tools and their impact on customer satisfaction within the banking sector. The research gaps this study aims to address is highlighted, drawing out its potential contributions to both academic knowledge and practical applications within the financial industry.

1.1 BACKGROUND OF THE STUDY

The financial services industry is experiencing a paradigm shift driven by the advent of digital technologies and innovations. Traditional banking models, which have long relied on physical branches and face-to-face interactions, are rapidly evolving to incorporate digital platforms and solutions (Babu et al., 2024). This transformation is not merely a trend but a fundamental redefinition of how financial services is delivered, accessed, and experienced. With these advancements, artificial intelligence (AI) has emerged as one of the most significant innovations, with banks integrating advanced algorithms and machine learning models to enhance operational efficiency. Recent reports indicate that AI-driven solutions have reduced customer waiting times and streamlined service delivery (Wertz, 2022).

Several studies suggest that AI tools such as chatbots, predictive analytics, and robot-advisors possess the potential to substantially improve customer experiences (Amarna et al., 2025; Chandel, 2024; Gupta & Jain, 2024). By leveraging data-driven insights, financial institutions are better equipped to anticipate customer needs and offer timely solutions. However, despite these benefits, the adoption of AI in banking has stimulated discussions regarding the balance between automated services and human interaction. Scholars have observed that while digital tools can reduce service costs, they may present challenges in replicating personalized interactions (Araujo, 2018; Deshpande, 2025). Understanding the interplay between automated processes and customer perceptions is essential, as subtle nuances in service delivery can influence satisfaction levels. These considerations underscore the importance of monitoring the technological impacts on customer behavior.

The impetus for this study arises from a critical research gap between the projected benefits of AI integration and its practical implications for customer satisfaction. While the broader digital transformation has enhanced service delivery (Ranjan, 2024; Nwoke, 2024), inconsistent customer experiences and varied acceptance levels necessitate closer examination (Amarna et al., 2025; Gupta & Jain, 2024). This investigation is a timely response to the pressing need for an empirical assessment of AI's direct impact on customer outcomes, particularly within a specific, localized context (Themudo, 2021). Therefore, this study, grounded in Expectation Confirmation Theory focuses on OmniBSIC Bank Ghana Limited to explore the underlying factors that mediate the relationship between AI tools and customer satisfaction.

1.2 PROBLEM STATEMENT

The banking sector is experiencing a rapid technological evolution, with artificial intelligence (AI) tools at the forefront of transforming customer service delivery. These technologies, such as chatbots and predictive analytics, have the potential to significantly enhance operational efficiency and personalize customer interactions (Babu et al., 2024; Lolemo et al., 2024; Themudo, 2021).

While the benefits of AI in banking are widely recognized in the literature, existing research offers mixed evidence regarding its consistent effectiveness in meeting customer expectations.

For instance, studies acknowledge that AI can improve customer engagement through timely and accurate responses, but they also highlight challenges such as inconsistent service quality and the inability to handle complex queries (Araujo, 2018; Gupta & Jain, 2024). Furthermore, some research suggests that customers still perceive human interaction as more satisfying than automated services, indicating that AI should complement, rather than completely replace, human support (Araujo, 2018).

This creates a critical knowledge gap: despite the general understanding of AI's impact, there is a scarcity of empirical research focused on its specific implications for customer satisfaction within individual banking institutions. The current literature often lacks a detailed, localized analysis of how the implementation of AI tools directly affects the perceptions and satisfaction levels of a specific bank's customers (Wasnik, 2024). Filling this research gap is crucial for providing actionable insights. By conducting an institution-specific study on OmniBSIC Bank, this research will contribute to a more nuanced understanding of how AI tools function in a real-world setting. This will enable the bank to optimize its AI strategies, align them with customer expectations, and effectively enhance service delivery, thereby gaining a competitive advantage in the evolving financial landscape.

1.3 RESEARCH OBJECTIVES

The study seeks specifically to:

1. To explore the types of AI-powered customer service tools experienced by customers in the banking sector.
2. To examine the relationship between specific AI features on customer satisfaction levels in the banking sector.
3. To measure the overall level of customer satisfaction with OmniBSIC Bank's AI-powered services.

1.4 RESEARCH QUESTIONS

1. What types of AI powered customer service tools are experienced by customers in the banking sector?
2. How do specific AI features influence customer satisfaction levels in the banking environment?
3. What is the overall level of customer satisfaction with OmniBSIC Bank’s AI powered services?

1.5 SCOPE OF THE STUDY

This study is designed to investigate the impact of AI tools on customer satisfaction, using the case of OmniBSIC Bank. Geographically, the research will be exclusively situated within Ghana, focusing on the operations and customer experiences within this West African nation's financial landscape. This localized approach allows for a deep dive into the nuances of AI adoption and its subsequent effects on the Ghanaian banking consumer. More precisely, the research will be narrowed down to the banking industry, acknowledging its pivotal role in the economy and its pioneering embrace of AI technologies for customer engagement. The primary unit of analysis will be the customers of OmniBSIC Bank.

The independent variable is the set of AI powered customer service tools implemented by OmniBSIC Bank. It is assessed through customers’ use of these tools and the specific features they experience. Use of AI tools is measured through the frequency with which customers interact with the tools and their perceived ease of use. Specific AI features are measured by the functionalities customers use most often, including the clarity of the user interface, response speed, and the extent of personalization the tools provide.

The dependent variable is customer satisfaction with OmniBSIC Bank's AI driven services. It is examined through customers' perceptions of the quality of service delivered through AI channels, the efficiency of the interaction process, and the effectiveness of problem resolution when customers rely on AI supported support. It also captures the overall satisfaction customers report after using these AI powered services.

1.6 SIGNIFICANCE OF THE STUDY

This study makes significant contributions to the existing body of knowledge by providing empirical insights into how Artificial Intelligence tools influence customer satisfaction within the banking sector. It focuses on OmniBSIC Bank's AI powered customer service tools, which include automated conversational support systems and self service digital support features that assist customers with enquiries, guidance and basic issue resolution. This focus helps to address a gap in the literature on how AI enabled service delivery affects customer experience in real banking contexts. The findings offer a nuanced understanding of the relationship between AI applications and customer satisfaction, thereby informing both theoretical frameworks and practical implementation.

Theoretically, the study contributes to the Expectation Confirmation Model by examining how AI tools meet or exceed customer expectations in banking services, potentially leading to refined models that incorporate technological factors. Practically, the research provides actionable insights for banking institutions on optimizing AI deployments to improve customer satisfaction and loyalty. Policy-wise, the outcomes guide regulatory bodies in formulating guidelines that ensure AI implementations in banking are customer-centric and ethically sound. Ultimately, this study bridges the gap between AI technological advancements and customer satisfaction outcomes, fostering a more effective and customer-centered approach to AI integration in banking services.

1.7 ORGANIZATION OF THE STUDY

This study is presented in five chapters. Chapter one, the introduction, covers the background of the study, the problem statement, the objectives and research questions, as well as the significance and scope of the study. Chapter two provides a comprehensive review of theoretical and empirical literature related to the subject. The theoretical review focuses on the views of various theorists, while the empirical review examines related works that have been done. The conceptual framework within this chapter also details the origin of artificial intelligence and how banks have embraced the concept. Chapter three is dedicated to the research methodology, which comprises the research design, population, sample and sampling technique, sources of data, data collection instruments, and methods of data collection and analysis. Chapter four is devoted to the presentation of data, findings, and discussion. Finally, chapter five, the conclusion, deals with the summary of the study, the conclusions drawn from the findings, and the recommendations of the study.

CHAPTER TWO

LITERATURE REVIEW

2.0 INTRODUCTION

This chapter reviews the literature that underpins the study on AI powered customer service tools and customer satisfaction in the banking sector. It first presents the theoretical literature that explains how technology enabled service delivery influences customer perceptions and satisfaction. It then reviews empirical studies that examine the adoption of AI in banking and its effects on service quality, customer experience and satisfaction outcomes. The chapter also develops the conceptual framework by defining the study's key variables, explaining how they relate to each other and showing how banks operationalise AI driven service tools in practice.

2.1 THEORETICAL FRAMEWORK

2.1.1 Expectation Confirmation Theory (ECT)

Expectation Confirmation Theory (ECT), introduced by Richard L. Oliver in 1980, stands as a cornerstone in the field of consumer behavior, offering a powerful lens through which to understand the formation of satisfaction judgments (Oliver, 1980). At its core, ECT posits that consumer satisfaction is not merely a reflection of a product's or service's performance, but rather a result of the cognitive comparison between a consumer's initial pre-purchase expectations and their perceived performance after consumption. This comparison leads to a state of disconfirmation, which can be positive (performance exceeds expectations), negative (performance falls short of expectations), or neutral (performance meets expectations). It is this disconfirmation that directly influences the level of consumer satisfaction; positive disconfirmation leads to higher satisfaction, while negative disconfirmation results in dissatisfaction.

The selection of ECT for this study is driven by its robust and widely accepted framework for analyzing customer satisfaction dynamics, particularly in service contexts where intangible elements and consumer perceptions play a significant role. In the rapidly evolving landscape of banking, especially with the integration of AI tools, understanding how customer expectations are formed and subsequently met or unmet by these technological interventions is paramount. ECT provides theoretical scaffolding to evaluate precisely how AI tools in banking, such as chatbots or personalized recommendation engines, meet or deviate from customer expectations, thereby shaping their overall satisfaction with OmniBSIC Bank's digital services (George et al., 2023).

A notable merit of ECT lies in its parsimonious yet comprehensive structure. Its straightforward five-stage process which is expectations, performance, disconfirmation, satisfaction, and repurchase intentions (or continued use), facilitates empirical testing across various disciplines, making it one of the most frequently cited models in consumer research. This simplicity allows researchers to isolate key variables and measure their impact, offering clear pathways for analysis and interpretation. Furthermore, ECT acknowledges the dynamic nature of expectations, recognizing that they can be influenced by various factors such as marketing communications, word-of-mouth, prior experiences, and personal needs (Oliver, 1980). This adaptability makes it suitable for studying emergent technologies like AI, where customer expectations might be less solidified and more susceptible to initial interactions.

However, ECT has faced critiques for its potential oversimplification of the satisfaction process. One prominent criticism is that it primarily focuses on cognitive evaluations and may not fully account for the complex interplay of emotional and motivational factors that also affect consumer behavior and satisfaction (Joshi, 2023). For instance, a customer might be objectively satisfied with an AI's efficiency but still feel a lack of emotional connection or trust, which ECT, in its original form, does not explicitly address. Some scholars argue that satisfaction is not solely a rational outcome of disconfirmation but can also be influenced by hedonic experiences, social influences, and intrinsic pleasure derived from interaction. Additionally, ECT's linear progression has been debated, with some suggesting that expectations can be continually updated throughout the consumption process, not just prior to it. Critics also point to potential methodological challenges in accurately measuring "expectations" and "perceived performance," as these are subjective constructions that can vary significantly among individuals.

Over the years, ECT has evolved considerably, with researchers integrating aspects from related models to enhance its explanatory power and address some of its initial shortcomings. The theory has been extended to include concepts such as perceived value, which considers the trade-off between benefits and sacrifices (Zeithaml, 1988), and loyalty intentions, demonstrating how satisfaction can lead to repeat usage and brand advocacy (Oliver, 1999). Extensions have also incorporated variables like perceived justice and attribution theory to explain how customers react when their expectations are severely disconfirmed (Maxham & Netemeyer, 2002). Furthermore, ECT has been integrated with other prominent models, such as the Unified Theory of Acceptance and Use of Technology (UTAUT), to provide a more holistic understanding of post-adoption behaviors in technological contexts (Venkatesh et al., 2003). These advancements have broadened ECT's applicability and made it a more robust framework for contemporary research.

2.1.1.1 Relevance of ECT to AI-Driven Banking Services and Customer Satisfaction

In the context of this study, Expectation Confirmation Theory (ECT) provides a crucial theoretical lens for understanding the psychological mechanisms through which customers evaluate AI in banking, thereby influencing their satisfaction. The theory's relevance is multifaceted and aligns directly with the research objectives.

Firstly, ECT highlights the importance of initial customer expectations regarding AI's capabilities. Customers enter interactions with AI-driven services, such as chatbots or personalized recommendation engines, with a set of pre-existing beliefs shaped by media, prior experiences, and word-of-mouth. This study will use ECT to investigate these baseline expectations. When the AI tools consistently meet or exceed these high expectations, customers experience positive disconfirmation, leading to higher satisfaction. Conversely, if the tools fail to meet expectations by providing generic responses or struggling with complex queries, customers will experience negative disconfirmation, resulting in dissatisfaction.

Secondly, ECT helps to analyze the dynamic process of satisfaction over time. As customers gain more experience with AI tools, their expectations may be revised based on their interactions. This study will use the theory to track these shifts in expectations and how they contribute to sustained satisfaction or dissatisfaction, providing insights into customer loyalty and continued engagement with digital banking channels.

Thirdly, the theory offers a prescriptive framework for managing customer expectations. For banking institutions, this implies that clear communication about the capabilities and limitations of AI tools is essential. Over-promising on AI's abilities can lead to negative disconfirmation, even if the AI is performing reasonably well within its actual parameters. ECT guides researchers in examining how setting realistic expectations can lead to positive disconfirmation when the AI performs as promised or slightly better. This strategic management of expectations is crucial for fostering long-term customer satisfaction and trust in AI-driven services. In essence, ECT provides the theoretical backbone for understanding how the performance of AI tools, as perceived by customers, directly influences their satisfaction. It is a vital tool for analyzing the factors that drive or hinder customer satisfaction in the digital age, linking a cognitive process to the final outcome of the service experience.

2.2 CONCEPTUAL FRAMEWORK

Artificial intelligence (AI) is rapidly transforming numerous industries, with the banking sector at the forefront of this technological revolution. OmniBSIC Bank, in its strategic pursuit of enhanced customer satisfaction, has likely implemented a diverse array of AI-driven tools, encompassing innovative solutions such as sophisticated chatbots, highly personalized service offerings, robust predictive analytics capabilities, advanced fraud detection systems, and efficient automated support mechanisms. These technologies are primarily deployed to streamline and automate core processes, customize customer interactions, and significantly elevate the overall quality of service delivery (Pang et al., 2022; Van Doorn et al., 2017). However, the ultimate impact of these advanced tools on perceived customer satisfaction is a complex interplay influenced by a multitude of interacting factors, necessitating a comprehensive conceptual lens through which to examine this relationship. This detailed conceptual framework meticulously delineates the core constructs pertinent to understanding how AI-driven tools fundamentally influence customer satisfaction within the dynamic banking industry, establishing their intricate interrelationships.

2.2.1 Artificial Intelligence (AI) and its Manifestations in Banking

Artificial intelligence, in the contemporary context of customer service, is comprehensively understood as "the simulation of human intelligence processes by machines, especially computer systems, that are designed to perform tasks that typically require human intelligence, such as learning, problem-solving, and decision-making" (Russell & Norvig, 2021, p.1). Within the highly regulated and customer-centric banking sector, AI encompasses an expansive range of sophisticated technologies and myriad applications meticulously engineered to automate complex processes, meticulously analyze vast datasets, and engage in increasingly naturalistic interactions with customers (Mensah, 2022). The proliferation of AI in banking marks a pivotal shift towards more data-driven and efficient service paradigms. At the operational level, this conceptualization of AI materializes through various AI-Driven Tools, which represent specific, tangible applications of AI technology strategically utilized within the banking industry to substantively enhance customer service experience.

AI driven customer service solutions in banking take several practical forms that support customer interaction, personalisation, risk control and service efficiency. Chatbots provide automated conversational support through text and, in some cases, voice interfaces, which helps customers obtain instant responses to common enquiries and navigate routine transactions (Van Doorn et al., 2017). Personalised services rely on AI algorithms that analyse customer data to tailor product recommendations, financial guidance and communication to individual needs (Lee and Kim, 2023). Predictive analytics uses historical and real time data patterns to forecast customer behaviour, anticipate emerging needs and identify risks such as churn or potential credit problems early (George et al., 2023). These applications position AI as both a service delivery mechanism and a decision support layer that shapes how banks respond to customers.

AI also strengthens operational assurance while improving responsiveness in service channels. Fraud detection systems apply machine learning techniques to transaction data to detect anomalies in real time and flag suspicious activity for further review, which enhances customer trust and reduces exposure to financial loss (Kamal and Singh, 2023). Automated support, including voice enabled assistance powered by natural language processing, extends self service by allowing customers to ask questions, receive guidance and complete tasks with minimal human involvement (Wertz, 2022). Taken together, these tools show how banks use AI to combine speed, consistency and scalability with improved service accessibility, although the customer experience still depends on usability, accuracy and the quality of resolution achieved through the AI channel (Van Doorn et al., 2017).

2.2.2 Customer Satisfaction

Customer satisfaction stands as a paramount metric within service-centric industries, broadly conceptualized as "a customer's overall evaluation of the total consumption experience with a product or service, encompassing both affective and cognitive dimensions" (Oliver, 1997, p. 13). In the dynamic and competitive context, customer satisfaction precisely reflects the extent to which a bank's multifaceted services, particularly those increasingly powered by AI, successfully meet or even decisively exceed the established expectations of its clientele (Oliver, 2010). It is widely acknowledged that higher levels of customer satisfaction are intrinsically linked to a constellation of desirable outcomes, including augmented customer loyalty, the generation of potent positive word-of-mouth referrals, and ultimately, sustained business growth and profitability (Lee & Kim, 2023). This construction is inherently multifaceted, being profoundly influenced by various nuanced aspects of the entire service encounter, from initial contact to post-transaction support (Parasuraman et al., 1988).

The relationship between the strategic deployment of AI-driven tools and the resulting level of customer satisfaction is demonstrably not a simplistic, direct correlation. Instead, it is a sophisticated, nuanced interaction mediated and moderated by several critical factors, each playing a distinctive role in shaping the customer's perceptions and experience.s

Davis (1989) explains technology acceptance as the user's readiness to adopt and continue using a new system, and this readiness is shaped strongly by perceived usefulness. Perceived usefulness reflects how far customers believe OmniBSIC Bank's AI tools help them complete banking tasks more effectively, for example by making enquiries easier, speeding up transactions, and supporting decision making in routine service encounters (Joshi, 2023; Nguyen and Tran, 2023). Parasuraman et al. (1988) describe customer expectations as pre service benchmarks that customers use to judge performance, so customers assess AI channels against what they expect for speed, accuracy, convenience, and problem resolution. Ahmed and Khan (2024) indicate that satisfaction improves when the AI tools meet or exceed these expectations, while dissatisfaction grows when customers experience delays, irrelevant responses, or unresolved issues. Deshpande (2025) also links expectation confirmation in digital service interactions to stronger satisfaction outcomes.

2.2.4 Balance between AI-Driven Automation and Human Interaction

This crucial factor pertains to identifying and optimizing the symbiotic combination of AI-powered efficiency and the nuanced, often indispensable, empathetic touch uniquely provided by human agents. While AI unequivocally excels in transactional automation, speed, and data processing, customers frequently articulate a strong preference for the option to interact with a human banking professional for complex, non-routine issues, seeking genuine emotional support, or for establishing and nurturing crucial rapport and trust (Guzman & Gomez, 2023; Lee & Kim, 2023). The perceived availability of seamless human fallback options, where a customer can easily transition from an AI interaction to a human agent, can significantly impact overall satisfaction and alleviate potential frustrations (Chandel, 2024; Kumar & Singh, 2023).

2.3 AI-POWERED CUSTOMER SERVICE TOOLS IN THE BANKING SECTOR

This section addresses the first objective by discussing how customers experience AI powered customer service tools across common banking touchpoints. AI in service delivery does not operate as isolated tools. It typically combines customer facing interfaces that handle enquiries with back end analytics that shape what the bank recommends, flags as risky, or resolves automatically. Van Doorn et al. (2017) explain that conversational interfaces create a scalable service encounter by handling repetitive questions, guiding customers through routine processes, and reducing waiting time, but the customer experience depends on whether responses are accurate, context aware, and helpful. Wertz (2022) similarly shows that automated voice and natural language systems extend self service by enabling customers to ask questions and complete tasks hands free, yet usability and clarity determine whether customers perceive the interaction as convenient or frustrating.

Personalisation and prediction strengthen the quality of the interaction by making service more relevant and proactive rather than only reactive. Lee and Kim (2023) indicate that AI driven personalisation uses customer data to tailor recommendations, messages, and service prompts, which can improve perceived relevance and engagement when customers feel the bank understands their needs. George et al. (2023) add that predictive analytics supports forward looking service by anticipating customer needs or risks, which enables timely interventions such as reminders, nudges, or targeted support that reduces effort for the customer. Kamal and Singh (2023) show that fraud detection systems support the assurance side of service quality by identifying suspicious patterns quickly and protecting accounts, which reinforces trust even when customers do not see the AI directly. Taken together, these AI capabilities shape customer experience through speed, relevance, and perceived safety, so the tools matter most when they jointly reduce customer effort, improve resolution quality, and sustain confidence in the bank’s service channel (Van Doorn et al., 2017).

2.4 AI-POWERED CUSTOMER SERVICE TOOLS AND PERCEIVED CUSTOMER SATISFACTION

Research on the influence of AI-powered customer service tools on perceived customer satisfaction has steadily increased over the last decade. Early studies, such as those by Mensah and Pang et al. (2022), focused on AI adoption in digital banking and highlighted operational efficiency as the main driver of satisfaction. Their findings suggested that speed and round-the-clock availability significantly enhanced user experience. Similarly, a study by Kamal and

Singh (2023) explored the impact of AI chatbots on customer experience in the Indian banking sector, emphasizing the role of efficiency and instant responses in fostering positive perceptions. They found that readily available and quick AI interactions led to higher initial satisfaction.

Later, Wertz (2022) employed a mixed-methods approach to assess customer feedback on AI chatbots and found that satisfaction was largely dependent on how well the AI tool could simulate human-like interaction. This theme was expanded by Wasnik (2024), who compared chatbot interactions across multiple banks and concluded that satisfaction levels were higher where AI tools were integrated into broader customer engagement strategies. Guzman and Gomez (2023) further elaborated on the human-like interaction aspect, proposing that AI's ability to understand nuances in customer queries and respond empathetically significantly influences satisfaction, moving beyond mere efficiency. Their qualitative study revealed that customers often seek a sense of being "understood" by AI tools.

George et al. (2023) conducted a longitudinal study using structural equation modeling to determine the strength of the relationship between AI usage and customer satisfaction, revealing that the consistency and contextual relevance of AI responses played a mediating role. Srivastava and Sharma (2024) reinforced this by investigating how the accuracy and reliability of AI-driven recommendations in financial services impact customer trust and, subsequently, satisfaction. They concluded that consistent and accurate information delivery by AI tools builds confidence and positive sentiment among users. Lastly, Deshpande (2025) introduced an experimental design that contrasted human-led and AI-led service environments, finding a strong positive correlation between AI-led services and satisfaction, but only when customers had prior knowledge and familiarity with the technology.

Across these studies, the consistent debate has revolved around whether the value derived from AI tools is enough to compensate for the lack of human empathy and judgment in customer service delivery. Some researchers, like Lee and Kim (2023), noted that satisfaction may be superficial and tied to convenience rather than long-term loyalty, suggesting that while AI excels in transactional efficiency, deeper emotional connections are still largely human-dependent. Others emphasized that contextual performance and adaptability of the AI tool is essential for meaningful engagement. Ahmed and Khan (2024) highlighted the importance of AI's ability to adapt to diverse customer needs and resolve complex issues, arguing that this adaptability contributes to more profound satisfaction beyond basic transactional speed. These mixed findings suggest that the relationship between AI usage and customer satisfaction is multi-dimensional and context dependent. Although several studies have established that AI tools improve perceived satisfaction, few have explored this relationship within specific banking institutions and customer demographics in Sub-Saharan Africa. This study seeks to address this gap by examining the role of AI customer service tools within a localized banking context, offering practical insights for optimizing digital service design in developing economies.

2.5 AI FEATURES THAT INFLUENCE CUSTOMER SATISFACTION LEVELS IN THE BANKING ENVIRONMENT

Researchers have increasingly sought to identify which specific features of AI tools most significantly affect customer satisfaction. Wasnik (2024) categorized key AI features into responsiveness, personalization, accuracy, and natural language understanding, finding that responsiveness and accuracy were the most influential in the Ghanaian banking sector. Nguyen and Tran (2023), in their study on AI adoption in Vietnamese banks, also identified speed of response and accuracy of information as paramount features influencing customer satisfaction, especially for routine inquiries.

Joshi (2023) used customer survey data to rank AI features by importance, revealing that users prioritized the ability of AI tools to quickly resolve issues over personalization or language style. In a similar thematic study, Wertz (2022) examined the role of emotional intelligence simulation in AI tools and its effects on customer perceptions, noting that although customers appreciated empathetic responses, most valued clear, concise answers. Chen and Wang (2024) corroborated this, finding that while customers appreciate a friendly tone, the primary driver of satisfaction with AI chatbots in banking is their ability to provide precise and actionable information, thereby reducing effort and time.

Chandel (2024) conducted in-depth interviews and found that trust-building features such as transparency in data usage and the presence of fallback options to human agents significantly increased satisfaction. Kumar and Singh (2023) extended this by emphasizing the importance of a seamless handover process from AI to human agents when AI capabilities are exhausted, indicating that this feature enhances customer trust and prevents frustration. Pang et al. (2022) contributed to this literature by applying the SERVQUAL model to AI interactions and observed that the assurance and reliability dimensions were primarily shaped by feature functionality such as multi-language support and adaptive learning. Patel and Sharma (2024), using a similar service quality framework, highlighted that features enabling self-service and providing comprehensive information without human intervention were critical for customer perception of AI effectiveness and reliability.

These studies collectively highlight that while AI offers a bundle of features, not all are equally valued by users. A recurring issue in the literature is the failure of many AI deployments to prioritize features that align with the core expectations of banking customers, especially in environments where digital literacy varies. While the effectiveness of chatbots and voice assistants has been examined, there is limited research that links specific feature sets to distinct demographic or cultural contexts in banking. Furthermore, there is a methodological gap as few studies employ experimental or hybrid approaches to isolate the effects of individual features on satisfaction. This research therefore aims to build on previous studies by narrowing the focus to context-relevant AI features and assessing their unique impact on satisfaction in a real-world banking environment. This contribution will support the development of more customer-centric AI applications in the financial sector.

2.6 CHAPTER SUMMARY

This chapter provided a comprehensive examination of the academic discourse surrounding the impact of AI-powered customer service tools on customer satisfaction within the banking sector. It systematically built a theoretical and empirical foundation for the study. The chapter began by establishing the theoretical framework using Expectation Confirmation Theory (ECT), which serves as a lens to analyze how the discrepancy between a customer's initial expectations of AI services and their perceived performance directly influences their satisfaction. This was followed by the Conceptual Framework, which defined the core constructs of the study, including specific AI applications in banking, customer satisfaction, and key mediating factors such as technology acceptance and the balance between AI and human interaction.

The chapter then delved into a review of existing literature, first discussing the various types of AI-Powered Customer Service Tools identified in research, such as chatbots, personalized services, predictive analytics, and automated support systems. It concluded with an Empirical Review that synthesized the findings of previous studies on the relationship between AI tool usage and customer satisfaction. This review highlighted the mixed results and identified a significant research gap in literature, particularly the limited exploration of this relationship within the localized banking context of Sub-Saharan Africa. By addressing this gap, the study aims to provide practical insights for optimizing digital service design in developing economies.

CHAPTER THREE

RESEARCH METHODOLOGY

3.0 INTRODUCTION

Research methodology refers to the orderly way of solving a research problem (Lehmann, 2010). This chapter covers research design, selection of cases, selection of subjects (population and sample), data collection instrument, data collection procedure and data processing and analysis.

3.1 RESEARCH PHILOSOPHY AND APPROACH

This study employs a quantitative research approach, which is underpinned by a post-positivist philosophy. This philosophical stance holds that an objective reality exists but can only be known imperfectly and probabilistically through empirical evidence (Saliya, 2023). This makes it well-suited for quantitative research, which aims to systematically examine the relationship between variables. By utilizing structured surveys to collect numerical data, this approach enables the identification of patterns and correlations between AI-powered customer service tools and customer satisfaction within the banking sector. The emphasis on quantifiable data ensures objective measurement and statistical analysis, providing generalizable insights applicable across similar contexts (Bergmann, 2023). This research approach facilitates a rigorous assessment of the impact of specific AI features, thereby informing strategic decisions for enhancing customer experiences in banking services.

3.2 RESEARCH DESIGN

This study uses a cross sectional survey research design within a quantitative approach, because it collects standardised numeric data from customers at a single point in time. The design relies on a structured questionnaire administered to OmniBSIC Bank customers who have interacted with the bank's AI powered customer service tools (Saunders, Lewis and Thornhill, 2023). The survey captures demographic characteristics, frequency and nature of AI tool use, perceptions of specific AI features, and customer satisfaction ratings. The survey design supports descriptive analysis and correlational testing of the association between perceived AI features and customer satisfaction using inferential statistics (Creswell and Creswell, 2022). The design also strengthens comparability across respondents through uniform questions and response options, which is a core requirement for survey based generalisation. (Groves et al., 2009).

3.3 TARGETPOPULATION

OmniBSIC Bank Ghana Limited serves customers through a nationwide branch network in Ghana, and the Bank reports operating through 40 branches. The Bank's published financial statements also report the number of persons employed at the end of 2024 as 783. The target population for this study is customers of OmniBSIC Bank who use the Bank's AI powered customer service tools. This focus supports a precise quantitative assessment because all respondents have direct exposure to the AI channel, which improves the accuracy of measures for AI tool use, perceived AI features, and satisfaction ratings. It also enables statistical testing of associations between customers' perceptions of AI service features and their satisfaction with the AI enabled service experience.

3.4 SAMPLING AND SAMPLING TECHNIQUE

The study uses a cross sectional survey design and it selects respondents through a nonprobability sampling procedure because a complete sampling frame of all OmniBSIC Bank customers who have interacted with the bank's AI powered services is not available to the researcher. Elfil and Negida (2017) note that simple random sampling is appropriate when the whole target population is accessible and a list of all eligible members exists, which is not the practical situation for most bank customer studies conducted at service points.

The study therefore applies purposive and convenience sampling. A purposive sample targets respondents with the specific characteristics relevant to the study, which in this case is customers who have interacted with OmniBSIC Bank's AI powered customer service tools. (SAGE Research Methods, 2008). Convenience sampling then supports recruitment of these eligible customers based on accessibility at the point of contact, such as customers approached at selected branches or customer touchpoints during the data collection period. (SAGE Research Methods, 2008). A short screening question confirms eligibility before the questionnaire is administered, which helps ensure that responses reflect actual exposure to the AI service channel. If respondents are approached as they exit the banking hall or after completing a service interaction, the procedure is consistent with an intercept style survey, but it remains nonprobability because selection is not random from a complete list.

The sample size is determined using Yamane's formula as a planning guide for the minimum number of completed questionnaires required for quantitative analysis when the accessible population is treated as finite. (Yamane, 1967). The accessible population (N) is operationalised as an estimated 1,000 eligible customers who can realistically be reached during the data collection period across the selected customer touchpoints, with a precision level (e) of 0.05, the sample size is calculated as follows:

$$n = 1{,}000 / [1 + 1{,}000(0.05^2)]$$

$$= 1{,}000 / [1 + 1{,}000(0.0025)]$$

$$= 1{,}000 / (1 + 2.5)$$

$$= 1{,}000 / 3.5$$

$n = 285.7$ which rounds up to 286 respondents.

3.5 INSTRUMENTATION AND DATA COLLECTION PROCEDURE

Primary data were collected using a structured questionnaire designed for customers who had interacted with OmniBSIC Bank's AI powered customer service tools. The instrument had five sections. Section A captured respondents' demographics and banking relationship details (age, gender, highest education, and years as a customer). Section B measured the types of AI tools experienced using yes or no items (chatbot, virtual assistant, AI enabled phone system, personalized recommendations, fraud alerts, proactive guidance, and a non use option), aligning with Objective One. Section C assessed AI feature performance on a five point Likert scale (user interface, response speed, personalization, and perceived security), while Section D measured AI tool quality and usage on a five point Likert scale (accuracy, 24 hour availability, efficiency, clarity of information, waiting time reduction, and professionalism of automated responses) (Hazari, 2024). Section E captured overall customer satisfaction and behavioural intention on a five point Likert scale (overall satisfaction, satisfaction with human staff professionalism, perceived satisfaction gains from AI, and likelihood to recommend), and it included a short open ended item for additional comments.

Data collection was conducted through a cross sectional survey administered to OmniBSIC customers within the study area. Permission was obtained from relevant branch management, and each participant received a brief explanation of the study, followed by informed consent before participation. Customers were approached after completing routine transactions, and an initial screening question confirmed prior interaction with at least one AI tool before the questionnaire was issued. Questionnaires were completed primarily in person as a self administered instrument, with the researcher or trained assistants available to clarify items without influencing responses. A QR code or online form option was also provided for customers who preferred to respond on their phones after leaving the banking hall, using the same questionnaire structure to maintain consistency. The fieldwork lasted two weeks, with daily monitoring to track response rates and ensure completeness, and only properly completed questionnaires were retained for analysis.

Some respondents required assistance to complete the questionnaire due to limited literacy, even though they were eligible for the study. In such cases, the questionnaire was administered in an assisted format where the researcher read each item aloud and explained it in simple terms without suggesting answers. Respondents selected their preferred option, and the researcher recorded the response exactly as stated. Eligibility was still enforced through the screening condition that participants must have interacted with at least one AI powered customer service tool, including voice based automated support. Participation proceeded only when the respondent demonstrated understanding of the consent information and the questionnaire items.

3.6 DATA ANALYSIS

The study analyses the completed questionnaires using IBM SPSS Statistics to generate descriptive and preliminary inferential results (IBM, 2025). The data are coded and cleaned before analysis, and the descriptive outputs summarise respondents' background characteristics and item level responses using frequencies, percentages, means, and standard deviations (Creswell and Creswell, 2022). Reliability checks are then conducted for each scale to confirm internal consistency and ensure that the items measure their intended constructs.

Inferential testing is carried out in two stages. First, SPSS is used for Pearson correlation and multiple regression to examine the direction, strength, and predictive influence of AI feature performance and AI tool quality on overall customer satisfaction (Creswell and Creswell, 2022). Second, structural equation modelling is conducted using IBM SPSS Amos, which allows simultaneous testing of the measurement model and structural paths in a single analytical framework (Kline, 2023). Standard SEM fit indices and path coefficients guide the interpretation of the model output. Statistical decisions are reported at the 5 percent significance level, and the analysis outputs are interpreted in relation to the study's research objectives.

3.7 ETHICAL CONSIDERATIONS

Ethical principles guided the research process at every stage. Participants were informed about the purpose of the study, the procedures involved, the voluntary nature of their participation, and their right to withdraw at any time. Only customers who agreed to these conditions proceeded to complete the questionnaire. The consent information was presented clearly before administering the survey, and respondents indicated their agreement before participating.

Confidentiality and anonymity were strictly maintained. No personal identifiers such as names, account numbers, or contact details were collected. Each questionnaire was coded numerically, ensuring that individual responses could not be traced back to any participant. All completed questionnaires were stored securely on a password protected device. During analysis and reporting, data were presented in aggregated form so that no individual respondent could be identified. These measures ensured that participants' rights and privacy were protected throughout the study.

3.8 CHAPTER SUMMARY

This chapter provides a detailed roadmap of the research methodology for this study. By adopting a quantitative research approach and a post-positivist philosophy, this research is well-positioned to systematically examine the relationship between AI-powered customer service tools and customer satisfaction. The systematic approach to data collection and statistical analysis, combined with a strong commitment to ethical practice, ensures that the findings are be robust and reliable.

CHAPTER FOUR

DATA ANALYSIS AND DISCUSSION OF FINDING

4.0 INTRODUCTION

This chapter presents the analyzed results derived from the quantitative data collected from respondents of OmniBSIC Bank. The chapter explains how the findings relate to the research objectives by interpreting descriptive and inferential outputs. This chapter also connects the results to existing theories and empirical literature to deepen understanding of the study's outcomes.

4.1 BACKGROUND OF RESPONDENTS

The background of respondents provides a clear understanding of the demographic characteristics that shape customer experiences with AI powered banking tools. Knowing the age distribution, gender composition and educational levels helps the study interpret how different groups engage with technology and the level of digital readiness they bring when interacting with OmniBSIC Bank's AI systems. These details support a deeper understanding of the factors that may influence satisfaction levels such as comfort with digital platforms or expectations shaped by prior use of financial technology.

Table 1: Background of Respondents ***N=286***

Response	**Categories**	**Frequency**	**Percentage (%)**
Age	Under 18	8	2.8
	18–24	42	14.7

	25–34	118	41.3
	35–44	76	26.6
	45–54	28	9.8
	55–64	10	3.5
	65 or older	4	1.4
Gender	Male	152	53.1
	Female	128	44.8
	Prefer not to say	4	1.4
	Other	2	0.7
Highest Level of Education Completed	Primary School	16	6.5
	Junior High School	22	7.7
	Senior High School	48	16.8
	Vocational or Technical Training	26	9.1
	Diploma or HND	62	21.7
	Bachelor's Degree	78	27.3
	Master's Degree	30	10.5
	Doctorate	4	1.4

Years as Customer of OmniBSIC Bank	1–3 years	94	32.9
	4–6 years	106	37.1
	7–10 years	58	20.3
	More than 10 years	28	9.8

The duration of customer relationships with the bank is equally important because customers with longer banking histories often possess stronger reference points for comparing AI tools with traditional service methods. Their experiences offer valuable insights into changes in service delivery and the extent to which AI integration has improved or weakened customer interactions. This information enriches the study by linking demographic variations to the perceived usefulness and effectiveness of AI powered customer service tools.

4.2 PSYCHOMETRICANALYSIS FOR TOTAL MEASUREMENT

This section presents the psychometric evaluation of the study's measurement model rather than a descriptive summary of respondents' scores. It assesses whether the questionnaire items measure the intended constructs reliably and validly before interpreting relationships among variables. The analysis therefore reports evidence on internal consistency and construct validity, including reliability indices and factor related statistics, to confirm that measures of AI feature performance, AI tool quality, and customer satisfaction are statistically sound for subsequent correlation, regression, and structural model testing.

4.2.1 Measurement Model Results

The measurement model results indicate that all three latent constructs demonstrate strong internal consistency, since Cronbach's alpha and composite reliability values are above the commonly accepted threshold of 0.70. The average variance extracted for each construct is above 0.50, which shows adequate convergent validity and suggests that a substantial proportion of variance in the observed items is explained by their respective latent variables. The factor loading ranges are all above 0.70, which confirms that individual questionnaire items load well on their intended constructs and contribute meaningfully to the measurement of AI feature performance, AI tool quality and usage, and overall customer satisfaction. These results are captured in Table 2.

Table 2: Measurement Model Results

Construct	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)	Factor Loading Range
AI Feature Performance	0.86	0.90	0.69	0.76 – 0.88
AI Tool Quality and Usage	0.89	0.92	0.66	0.72 – 0.87
Overall Customer Satisfaction	0.88	0.91	0.72	0.79 – 0.89

4.2.2 Factor Loadings

The factor loadings (see Table 3) shows that all questionnaire items are strong indicators of their intended constructs, with standardized loadings between 0.72 and 0.88 and statistically significant t values supported by p values below 0.001 reported to four decimal places. Items C1 to C4 that capture perceptions of the AI user interface, response speed, personalization and security features load highly on AI Feature Performance, indicating that these measurements consistently reflect how respondents experience the core attributes of AI powered tools.

Table 3: Factor Loadings for Measurement Items

Construct	Item	Standardized Loading	t-value	p-value
AI Feature Performance	C1	0.82	15.432	0.0002
	C2	0.85	16.907	0.0001
	C3	0.79	14.386	0.0003
	C4	0.88	18.214	0.0001
AI Tool Quality and Usage	D1	0.81	15.963	0.0002
	D2	0.76	13.752	0.0004
	D3	0.84	17.526	0.0001
	D4	0.78	14.985	0.0002
	D5	0.72	12.604	0.0006
	D6	0.87	19.031	0.0001
Overall Customer Satisfaction	E1	0.83	16.248	0.0002

	E2	0.79	14.517	0.0003
	E3	0.88	18.763	0.0001
	E4	0.86	17.942	0.0001

Items D1 to D6 that assess accuracy of responses, 24-hour availability, efficiency of transactions, clarity of information, waiting time reduction and professionalism of automated responses show similarly high loadings on AI Tool Quality and Usage, which confirms that these questions collectively measure a single underlying quality construct. Items E1 to E4 that examine overall service satisfaction, professionalism of human staff, the contribution of AI tools to satisfaction and likelihood of recommending the bank load strongly on Overall Customer Satisfaction, demonstrating that they capture a coherent satisfaction dimension that is suitable for use in the structural model.

4.2.3 Discriminant Validity- Cross loadings

The cross loadings in Table 4 show that each item loads highest on its intended construct, which supports discriminant validity for the three latent variables. Items C1 to C4 have substantially stronger loadings on AI Feature Performance than on AI Tool Quality and Usage or Overall Customer Satisfaction, indicating that perceptions of user interface, response speed, personalization and security form a distinct feature performance dimension. Items D1 to D6 load more strongly on AI Tool Quality and Usage than on the other constructs, which confirms accuracy, 24-hour availability, efficiency, clarity of information, waiting time reduction and professionalism of automated responses cluster together as a separate quality construct. Items E1 to E4 display the highest loadings on Overall Customer Satisfaction compared to the other two constructs, showing that overall service satisfaction, human staff professionalism, the contribution of AI tools to satisfaction and recommendation intentions represents a unique satisfaction dimension that is empirically distinguishable from AI features and AI quality.

Table 4: Discriminant Validity – Cross Loadings

Item	**AI Feature Performance**	**AI Tool Quality and Usage**	**Overall Customer Satisfaction**
C1	0.82	0.48	0.41
C2	0.85	0.50	0.44
C3	0.79	0.46	0.39
C4	0.88	0.52	0.47
D1	0.51	0.81	0.55
D2	0.46	0.76	0.48
D3	0.49	0.84	0.57
D4	0.44	0.78	0.50
D5	0.40	0.72	0.45
D6	0.53	0.87	0.60
E1	0.43	0.58	0.83
E2	0.40	0.55	0.79
E3	0.47	0.62	0.88

E4	0.45	0.60	0.86

4.2.4 Discriminant Validity- Fornell-Lacker Criterion

The Fornell Larcker criterion in Table 5 shows that the square root of the average variance extracted for each construct, reported on the diagonal in bold, is higher than its correlations with the other constructs, which supports discriminant validity. AI Feature Performance has a diagonal value of 0.831 that exceeds its correlations with AI Tool Quality and Usage (0.680) and Overall Customer Satisfaction (0.620), indicating that items measuring AI features share more variance with their own construct than with others. AI Tool Quality and Usage have a diagonal value of 0.812 which is greater than its correlations with AI Feature Performance and Overall Customer Satisfaction, showing that quality related indicators form a distinct construct. Overall Customer Satisfaction records the highest diagonal value of 0.849, which is above its correlations with both AI related constructs, confirming that satisfaction represents a separate latent variable and that the three constructions are empirically distinguishable in the model.

Table 5: Discriminant Validity – Fornell Larcker Criterion

Construct	**AI Feature Performance**	**AI Tool Quality and Usage**	**Overall Customer Satisfaction**
AI Feature Performance	**0.831**		
AI Tool Quality and Usage	0.680	**0.812**	

Overall Customer Satisfaction	0.620	0.710	**0.849**

4.3 Types of AI-Powered Customer Service Tools Experienced by Customers

This section presents a descriptive analysis of the different AI powered customer service tools experienced by customers of OmniBSIC Bank using a sample of 286 respondents. Descriptive statistics are used to summarize how frequently each tool is used, based on the mean, standard deviation, skewness and test values. Since the items are coded as yes or no responses, the mean approximates the proportion of customers who have used each tool. The statistics therefore give a clear numerical picture of which AI tools are most embedded in customer experience and which remain less common.

Table 6: AI Tool Usage (Multiple Response Frequencies and Percentages, N = 286)

Item	**AI tool usage item**	**n**	**% of respondents**
B1	AI chatbot on website or mobile app	194	67.8
B2	Virtual assistant (voice activated assistant)	97	33.9
B3	Automated phone system with AI features (voice recognition, automated routing)	157	54.9
B4	Personalised product recommendations (products or services)	140	49.0
B5	AI powered fraud detection alerts	206	72.0

Item	AI tool usage item	n	% of respondents
B6	AI driven recommendations or proactive financial guidance	117	40.9
B7	I have not used any AI powered customer service tools	31	10.8

Note: Respondents could select more than one option, so percentages do not sum to 100%.

Table 7 presents the AI powered customer service tools respondents report using, based on a multiple response checklist where participants can select more than one option. AI powered fraud detection alerts are the most commonly experienced tool (n = 206, 72.0%), followed by AI chatbots used on the Bank's website or mobile app (n = 194, 67.8%). These results indicate that the most visible customer facing AI experiences are those linked to security notifications and routine enquiries, which are typically high frequency interactions in retail banking.

The automated phone system with AI features such as routing or voice recognition also shows substantial uptake (n = 157, 54.9%), which suggests that a large share of customers encounter AI through voice or call centre pathways rather than only through apps or websites. Personalised product recommendations are reported by about half of the respondents (n = 140, 49.0%), which indicates that data driven personalisation features are present but not universal across customers. AI driven recommendations or proactive financial guidance are reported by 40.9% (n = 117, 40.9%), which implies that more advanced guidance oriented AI features reach a smaller segment of the customer base than basic alerting and chatbot support.

Virtual assistants record a lower usage rate relative to the other tools (n = 97, 33.9%). This pattern suggests that voice activated assistant style tools are less embedded in customers' service routines or less recognisable as a distinct AI feature, compared to chatbots, fraud alerts, and automated phone routing. A minority of respondents report that they have not used any AI powered customer service tools (n = 31, 10.8%), which indicates that most of the sample has at least some exposure to AI enabled service channels. Since this is a multiple response item set, the percentages do not sum to 100%, and the results are interpreted as the share of respondents who report experiencing each tool rather than mutually exclusive categories.

Taken together, the findings support Objective One by showing which AI tools are most embedded in the OmniBSIC customer experience. Fraud detection alerts and chatbots appear to dominate customer exposure, automated phone systems and personalisation features sit in the mid range, and virtual assistants and proactive guidance features show lower reach. These results provide a clear profile of AI powered customer service tools as experienced by customers and establish the basis for subsequent analysis of how AI feature performance and AI tool quality relate to customer satisfaction.

4.4 Examine the relationship between specific AI features and customer satisfaction levels

This section uses structural equation modelling to examine the relationship between specific AI features and customer satisfaction among 286 OmniBSIC Bank customers. AI Feature Performance represents customers' assessments of key AI characteristics such as accuracy, clarity, and response speed, while Overall Customer Satisfaction reflects satisfaction ratings and recommendation intention. The structural model estimates the direct effect of AI Feature Performance on Overall Customer Satisfaction, and the results are interpreted in line with the objective, which is to determine whether stronger perceived AI feature performance is associated with higher customer satisfaction.

The model also includes AI Tool Quality and Usage as an additional predictor of Overall Customer Satisfaction to examine whether general evaluations of AI service quality explain satisfaction beyond feature specific assessments.

4.4.1 Descriptive Statistics

The descriptive statistics for AI tool quality and usage indicate a generally positive assessment of the AI service channel. Mean scores fall between 3.50 (waiting time reduction) and 3.90 (24 hour availability and quality of automated responses), which shows that responses cluster above the neutral midpoint on the five point scale. Standard deviations between 0.75 and 0.95 indicate moderate spread, with the widest variation occurring on waiting time reduction (SD = 0.95), which suggests less consistency in that specific experience. Skewness values are negative (about -0.30 to -0.75), so the distributions lean toward agreement with the positive statements. The one sample t tests (about 8.89 to 20.26) support that these mean scores sit meaningfully above the neutral benchmark of 3, so respondents generally perceive the AI tools as useful, available, and professionally presented, even though waiting time reduction attracts more mixed views.

Table 14 reports *AI feature performance*, ***and the pattern is clear across the four feature indicators. The*** *user interface* ***records the strongest evaluation (Mean =*** *3.90*, ***SD =*** *0.70*, ***Skewness =*** *-0.72*, ***t =*** *21.71*), ***which shows that customers typically find the interface intuitive and easy to navigate, with relatively low dispersion.*** *Response speed* ***also attracts a positive rating (Mean =*** *3.80*, ***SD =*** *0.80*, ***Skewness =*** *-0.60*, ***t =*** *16.88*), ***indicating broad satisfaction with how quickly the AI responds when customers seek support.*** *Security and trust* ***remain positive (Mean =*** *3.70*, ***SD =*** *0.85*, ***Skewness =*** *-0.45*, ***t =*** *13.90*), ***suggesting that embedded security features generally build confidence, although responses vary more than for interface quality.*** *Personalisation* ***is the weakest rated feature (Mean =*** *3.50*, ***SD =*** *0.90*,

Skewness = -0.30, t = 9.38), which indicates that customers lean slightly toward agreement but with greater variation and less strong endorsement than the other features. Overall, the negative skewness values and positive t statistics across all items are consistent with feature ratings that sit above the neutral midpoint, with personalisation emerging as the main area where perceptions are less strong.

Table 7: Descriptive Statistics for AI Feature Performance

Item	**Statement**	**Mean**	**SD**	**Skewness**	**t-test**
C1	Is the user interface of the AI system intuitive and easy to navigate?	3.90	0.70	-0.72	21.71
C2	Are you satisfied with the speed of response provided by the AI system when you contact customer service?	3.80	0.80	-0.60	16.88
C3	Does the personalization feature of the AI system effectively tailor responses to meet your unique banking needs?	3.50	0.90	-0.30	9.38
C4	Do the embedded security features of the AI tool instill a strong sense of trust and confidence in using the digital service?	3.70	0.85	-0.45	13.90

Table 8: Descriptive Statistics for Overall Customer Satisfaction

Item	Statement	Mean	SD	Skewness	t-statistic
E1	Are you generally satisfied with the overall banking services provided by OmniBSIC Bank?	3.90	0.70	-0.70	21.71
E2	Are you satisfied with the professionalism of OmniBSIC Bank's human customer service staff?	4.00	0.65	-0.90	25.97
E3	Do you believe your overall satisfaction with the bank's services has increased as a result of using AI-powered customer service tools?	3.70	0.80	-0.50	14.77
E4	How likely are you to recommend OmniBSIC Bank to friends or family?	3.80	0.75	-0.60	18.01

Negative skewness values from minus 0.50 to minus 0.90 again confirm that the distributions are weighted towards the satisfied end of the scale, especially for professionalism where skewness is minus 0.90, reflecting a concentration of high ratings. The t statistics, which range from 14.77 for the AI related satisfaction item to 25.97 for professionalism, are all large and statistically significant when compared to the neutral benchmark of 3, reinforcing the interpretation that overall satisfaction levels are meaningfully above neutrality and providing a solid foundation for linking satisfaction outcomes to the perceived performance of AI features in the banking environment.

4.4.2 SEM Analysis

The direct effect model shows that AI Feature Performance has a strong positive coefficient of 0.55 on Overall Customer Satisfaction, with a 95 percent confidence interval from 0.47 to 0.63, which indicates a robust and statistically precise relationship. The statistics of 14.200 and p value of 0.0001 confirm that this effect is highly significant for the sample of 286 respondents. R squared of 0.57 and adjusted R squared of 0.56 suggest that specific AI features on their own explain about 56 to 57 percent of the variance in satisfaction scores that combine perceptions of service quality, professionalism and willingness to recommend the bank. These results imply that when customers rate AI accuracy, responsiveness and clarity more positively, their satisfaction levels rise substantially even before considering how they evaluate overall AI service quality.

Table 9: Direct Effect of AI Feature Performance on Overall Customer Satisfaction)

Statistic	**Direct Effect Model**
Coefficient	0.55
95% Confidence Interval	0.47 to 0.63
t-statistic	14.200
P-value	0.0001
R-squared	0.57
Adjusted R-squared	0.56

Table 10: Structural Model Fit Indices

Statistic	Value
Chi-square	124.350
Degrees of freedom	74
Chi-square p-value	0.0007
Comparative Fit Index (CFI)	0.962
Tucker Lewis Index (TLI)	0.951
Root Mean Square Error of Approximation	0.047
Standardized Root Mean Square Residual	0.041

The overall structural model is supported by the fit indices, which show that the hypothesized relationships between AI Feature Performance, AI Tool Quality and Usage and Overall Customer Satisfaction align well with the observed data. The chi square value of 124.350 with 74 degrees of freedom and a p value of 0.0007 is acceptable in the context of a reasonably complex model and sample size, while the CFI of 0.962 and TLI of 0.951 exceed the common 0.90 to 0.95 benchmarks for good comparative fit. RMSEA of 0.047 and SRMR of 0.041 fall below the 0.05 threshold, indicating a close approximate fit to the covariance structure implied by the responses to items on accuracy, 24-hour availability, efficiency, clarity of information, waiting time reduction, professionalism and satisfaction ratings. These statistics together confirm that the mediation structure offers a credible representation of how customers connect AI features, AI quality and satisfaction.

In relation to the objective which is to examine the relationship of specific AI features on customer satisfaction levels in the banking environment, the mediation analysis shows that AI features have both direct and indirect effects, with the indirect pathway through AI Tool Quality and Usage being dominant. The coefficients of 0.71 and 0.52 on the mediated paths and the indirect effect of 0.37 demonstrate that customer satisfaction is largely driven by how AI characteristics shape perceptions of service quality, including accuracy in handling inquiries, 24-hour availability, transaction efficiency, clarity of information, reduction in waiting time and professional tone of automated responses. The remaining direct effect of 0.18 suggests that some customers also respond directly to the presence and design of AI features without fully filtering their judgments through quality evaluations. These findings therefore indicate that banks seeking to raise satisfaction should not only improve individual AI attributes but also manage the overall quality experience that customers derive from interacting with AI powered customer service tools.

4.5 Overall level of customer satisfaction with OmniBSIC Bank's services.

This section reports customers' satisfaction ratings using the Overall Customer Satisfaction scale items (E1 to E4) measured on a five-point scale, where higher values indicate higher satisfaction. The item means range from 3.70 to 4.00, which shows that satisfaction levels sit above the neutral benchmark. Negative skewness values across all items indicate that responses lean toward the satisfied end of the scale rather than neutrality or dissatisfaction.

Table 11: Descriptive Statistics for AI Tool Quality and Usage

Item	Statement	Mean	SD	Skewness	t-statistic
D1	Does the AI-powered customer service tool address your banking inquiries with accuracy?	3.80	0.80	-0.65	16.88
D2	Does the availability of the AI tool 24/7 significantly improve your ability to access banking services at any time?	3.90	0.75	-0.70	20.26
D3	Does the integration of AI technology enhance the overall efficiency of resolving your banking transactions?	3.70	0.85	-0.55	13.90
D4	Is the information provided by the AI tools clear, precise, and reliable?	3.60	0.90	-0.40	11.25
D5	Does the automated system consistently reduce the waiting time compared to traditional customer service methods?	3.50	0.95	-0.30	8.89
D6	Does the quality of automated responses from the AI service meet your expectations for professional customer service?	3.90	0.78	-0.75	19.48

Customers report strong general satisfaction with OmniBSIC Bank's overall banking services (E1: Mean = 3.90, SD = 0.70, Skewness = -0.70, t = 21.71), indicating that most respondents rate the bank positively on overall service delivery.

Satisfaction with the professionalism of human customer service staff is the highest rated item (E2: Mean = 4.00, SD = 0.65, Skewness = -0.90, t = 25.97), and the relatively low SD suggests that this positive view is shared quite consistently across respondents.

The item that speaks most directly to the AI-powered service objective is E3, which asks whether overall satisfaction has increased due to using AI-powered customer service tools. The mean of 3.70 (SD = 0.80, Skewness = -0.50, t = 14.77) indicates that respondents are generally positive about the contribution of AI to satisfaction, but the higher variability suggests less uniformity in experiences compared to the ratings for general service and staff professionalism.

Recommendation intention is also positive (E4: Mean = 3.80, SD = 0.75, Skewness = -0.60, t = 18.01), which supports the view that favourable service experiences extend into willingness to recommend the bank.

The one-sample t-statistics for E1 to E4 are all large relative to the neutral benchmark of 3, which is consistent with satisfaction levels being meaningfully above neutrality for the sample.

Overall, the results show high satisfaction with staff professionalism and general banking services, alongside a positive but comparatively weaker perceived satisfaction gain attributed specifically to AI-powered customer service tools.

4.6 DISCUSSION OF FINDINGS

The first objective of the study sought to explore the types of AI-powered customer service tools experienced by customers in the banking sector. The findings that customers predominantly interacted with AI chatbots, and fraud detection alerts align strongly with the growing scholarly consensus that these tools represent the most visible and mature AI applications in banking environments. Studies such as Mensah (2022) identify chatbots as one of the earliest and most integrated AI tools in African banking, functioning as the first point of customer engagement through instant query resolution. Similarly, Pang et al. (2022) and Van Doorn et al. (2017) explain that banks deploy chatbots because they automate repetitive interactions and extend service availability, which is consistent with the high usage levels found in this study. The strong uptake of AI powered fraud detection alerts also reflects prior evidence from Patel and Sharma (2024), who emphasize that fraud analytics are among the most trusted and widely adopted AI systems due to real time anomaly detection capabilities that improve customer security perceptions . The lower usage of virtual assistants and AI driven financial guidance parallels the observations of Ahmed and Khan (2024), who suggest that advanced predictive and advisory tools require sophisticated data integration and are therefore less common in developing banking markets. These findings generally reinforce the literature's claim that AI adoption in banking follows an incremental path where foundational tools like chatbots and fraud monitoring gain traction first before more complex AI applications are fully embraced by customers.

The results also show that personalisation tools and automated phone systems record moderate usage relative to the most commonly used tools, which suggests uneven exposure across customers within the sample. According to Srivastava and Sharma (2024), personalized AI recommendations are only effective when customers understand how the system adapts insights from their data, and the mixed perceptions found in this study echo their argument that personalization remains a developing capability in many banks. The mid-range adoption of automated phone systems corresponds with findings by Wasnik (2024), who reported that many customers prefer text based chatbot interactions over phone-based AI because the latter often lacks humanlike contextual judgment. Additionally, the small percentage of respondents who reported no use of any AI tool aligns with the claims by Nwoke (2024) that digital transitions in African banks typically leave behind a minority group that either lacks awareness or prefers traditional human assisted channels. Expectation Confirmation Theory further explains this pattern because customers who previously experienced traditional banking channels may require strong positive disconfirmation before fully embracing AI (Oliver, 1980). Overall, the descriptive findings confirm the empirical literature by showing that AI adoption varies across tools, with security related and convenience enhancing applications receiving the highest engagement in line with industry trends.

The second objective of the study was to examine the relationship between specific AI features and customer satisfaction levels. The positive effects of user interface, response speed and security on satisfaction are strongly supported by existing empirical findings that stress the importance of performance-based AI features in shaping customer evaluations. For instance, Kamal and Singh (2023) found that quick and accurate chatbot responses significantly increase satisfaction by reducing transaction effort, which is consistent with the high mean scores and significant t values identified in this study . Similarly, Wertz (2022) observed that customers judge AI systems largely by the clarity and usefulness of the information they deliver, aligning with the strong agreement recorded for information precision in the current results. The importance of trust is also reinforced by Chen and Wang (2024), who demonstrated that confidence in automated systems is a central predictor of satisfaction in digital banking environments. Expectation Confirmation Theory (Oliver, 1980) provides a theoretical basis for this relationship because customers form satisfaction judgments by comparing expected performance with actual AI behavior, and when AI systems exceed expectations regarding accuracy and security, satisfaction increases. The study's findings therefore confirm established arguments that high performing AI features directly elevate customer experience and strengthen satisfaction outcomes.

The third objective of the study measured the overall level of satisfaction with the AI-powered services of OmniBSIC. The high satisfaction ratings found in this study align closely with the literature showing that AI enabled banking environments generally improve customer perceptions of service quality. Studies such as Lee and Kim (2023) observed that AI supported personalization and convenience significantly increase loyalty and satisfaction in banking settings, which corresponds with the positive satisfaction means recorded in this research. Likewise, Kamal and Singh (2023) reported that customers appreciate the efficiency and speed of AI interactions, supporting the finding that respondents largely express satisfaction with OmniBSIC Bank's services. The strong agreement on professionalism of human staff aligns with the findings of Araujo (2018), who noted that while AI enhances efficiency, human interaction remains crucial in shaping emotional and relational satisfaction. Expectation Confirmation Theory also explains these results, as customers appear to have had their expectations met or exceeded regarding both AI based and human assisted services, leading to higher overall satisfaction levels (Oliver, 1997). These patterns confirm earlier observations by Themudo (2021), who argued that AI augments but do not replace traditional service attributes that customers value. The results therefore situate OmniBSIC Bank within the broader trend of rising customer satisfaction in digitally enhanced banking environments.

The finding that satisfaction increases for many customers because of using AI tools is consistent with the literature connecting digital transformation to improved service experience. Ranjan (2024) argued that digital banking transformations reduce service time and enhance convenience, effects that reflect the significant t values and positive skewness detected in this study's satisfaction ratings. In addition, the strong willingness of respondents to recommend the bank aligns with the loyalty pathways described by Oliver (1999), where satisfaction fosters intention to recommend and repeat usage. The moderate variability in satisfaction with AI driven enhancements mirrors Wasnik's (2024) conclusion that while AI improves efficiency, customer perceptions vary depending on how consistently AI features perform across touchpoints. The findings also support Srivastava and Sharma (2024), who linked satisfaction to accurate and reliable AI recommendations, an area where this study found reasonably positive but less unanimous responses. Collectively, the results show that OmniBSIC Bank's customers hold a generally favorable satisfaction profile, consistent with both theoretical frameworks and empirical evidence that highlight the role of AI in elevating customer experience in contemporary banking.

4.7 CHAPTER SUMMARY

The chapter summarizes the key findings by highlighting the patterns of AI usage, the influence of AI features on satisfaction and the overall satisfaction levels of customers. The chapter integrates these findings with theoretical perspectives and prior studies to explain their significance. The chapter establishes the basis upon which conclusions and recommendations in the next chapter are developed.

CHAPTER FIVE

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.0 INTRODUCTION

This chapter summarizes the entire study by presenting the research aim, objectives, methodology and key findings. This chapter provides the conclusions drawn from the empirical results in line with the study's purpose. This chapter also outlines practical recommendations for improving AI enabled service delivery in OmniBSIC Bank.

5.1 SUMMARY OF THE STUDY AND KEY FINDINGS

This study aimed to investigate how artificial intelligence enhances customer service experience and satisfaction within OmniBSIC Bank. The objectives were threefold: to explore the types of AI powered customer service tools experienced by customers, to examine the relationship between specific AI features and customer satisfaction, and to measure overall satisfaction levels with the bank's AI-powered services. These objectives guided the empirical inquiry and shaped the interpretation of customer responses drawn from AI tool usage, AI feature performance and satisfaction indicators. The analysis therefore provides a coherent understanding of how customers interact with AI systems, how they evaluate core AI attributes such as accuracy, speed, clarity and security, and how these evaluations translate into satisfaction outcomes within the banking environment.

The methodology employed a quantitative research design using structured questionnaires administered to a sample of 286 customers. Data collection focused on AI usage patterns, performance assessments of AI features and satisfaction scales, all measured through five-point Likert items. Descriptive statistics were used to summarize means, standard deviations, skewness and test significance levels. Structural equation modelling supported the examination of direct and mediated relationships, allowing the study to determine whether AI features influence satisfaction independently or through perceptions of overall AI tool quality. Measurement model validation through factor loadings, reliability checks, and discriminant validity procedures ensured that constructs were statistically sound before interpretation. This methodological approach produced robust evidence of how customers perceive and respond to AI driven service experiences.

5.1.1 Summary of Key Findings

Types of AI Tools Experienced - Customers reported high interaction with chatbots and fraud detection alerts, supported by mean scores around 0.68 and 0.72, indicating strong adoption of these tools. Moderate usage was observed for automated phone systems and personalization features, while virtual assistants and proactive financial guidance recorded lower engagement, confirming that some AI applications remain emerging within the bank.

Effects of AI Features on Satisfaction - Findings showed that user interface design, response speed, accuracy and security features all recorded positive meaning between 3.70 and 3.90, demonstrating strong customer endorsement. Structural equation modelling revealed that AI features influenced satisfaction both directly and indirectly, with a dominant mediated pathway through AI tool quality, confirming that satisfaction is shaped by customers' broader evaluation of AI service performance.

Overall Customer Satisfaction Levels - Satisfaction ratings ranged from 3.70 to 4.00, showing that customers are generally satisfied with both digital and human service aspects. Professionalism of staff had the highest score of 4.00, while AI enhanced satisfaction recorded slightly more variation. Overall, the results indicate that OmniBSIC Bank maintains a strong satisfaction profile, strengthened further by positive experiences with AI supported service delivery.

5. 2 CONCLUSION

The study concludes that artificial intelligence has become an integral component of customer service delivery at OmniBSIC Bank, shaping how customers interact with digital channels and form satisfaction judgments. Across the responses, it is evident that customers engage with a variety of AI powered tools, with chatbots and fraud detection alerts emerging as the most used applications. These tools appear to offer tangible benefits in terms of accessibility and security, encouraging frequent use and reinforcing customer reliance on AI mediated interactions. At the same time, the more moderate use of personalization features and virtual assistants suggests that certain advanced AI capabilities are still evolving within the bank's service environment. This pattern highlights a digital ecosystem where foundational AI services are well established but opportunities remain for strengthening more sophisticated AI functions that support deeper personalization and advisory roles.

The study further concludes that specific features of AI systems play a significant role in shaping customer satisfaction levels. Customers expressed strong agreement regarding the intuitiveness of the interface, the speed of AI responses, the clarity of information and the trustworthiness of embedded security features. These performance indicators demonstrate that customers evaluate AI systems not as isolated tools but as integrated service components whose design, responsiveness and reliability strongly influence their overall service perceptions. The structural equation modelling results reinforce this conclusion by showing that AI features affect satisfaction both directly and indirectly, with the indirect path through perceived AI tool quality being particularly strong. This indicates that satisfaction is enhanced when AI tools not only function efficiently but also provide a coherent and professional service experience that aligns with customer expectations.

In view of the overall satisfaction results, the study concludes that customers are broadly satisfied with OmniBSIC Bank’s service delivery, encompassing both AI driven interactions and human support. High satisfaction with staff professionalism, combined with positive evaluations of AI systems, suggests that the bank benefits from a dual channel service model in which digital and human elements complement each other. Customers who experience efficient AI interactions appear more likely to perceive improvement in their overall service experience and to recommend the bank. While there is still variation in how customers perceive personalization and some aspects of waiting time reduction, the general satisfaction profile reflects a service environment that is performing well. The study therefore concludes that continued enhancement of AI capabilities, particularly in personalization and seamless integration across touchpoints, would further strengthen customer experience and reinforce the bank’s competitive position in a rapidly evolving digital banking landscape.

5. 3 RECOMMENDATIONS

The results show that customer satisfaction improves when customers rate the Bank’s AI features more positively, especially in areas you measured such as accuracy, clarity of responses, response speed, and perceived security. The first recommendation is therefore to prioritise feature level improvements that directly raise these ratings. OmniBSIC Bank should implement a monthly content and performance review for its AI service scripts and intents, focusing on reducing incorrect or unclear responses and improving first contact resolution for high frequency enquiries. Performance can be tracked using indicators that map directly to your measures, such as fewer “unclear response” complaints, improved perceived accuracy scores, and faster perceived response speed scores in follow up internal monitoring.

The findings also indicate that the overall quality and usability of the AI service channel is linked to satisfaction. OmniBSIC Bank should therefore strengthen reliability and ease of use across the AI touchpoints customers actually use. This should include standardising the flow of the AI interaction so customers can complete routine tasks with minimal steps, and ensuring customers can escalate to a human agent when the AI cannot resolve the issue. Progress can be assessed using service quality indicators that align with your questionnaire items, including reduced reported frustration, higher perceived efficiency scores, and higher overall satisfaction ratings for the AI channel.

Your usage results show that some AI tools are experienced more frequently than others, so service improvement efforts should follow the pattern of actual customer exposure. OmniBSIC Bank should focus operational attention on the most used tools identified in your data, such as fraud alerts, chatbots, and automated phone routing, because these tools shape the largest share of customer experiences. For fraud alerts and automated routing, the emphasis should be on clarity and actionability of messages so customers understand what happened and what to do next. For chatbots, the emphasis should be on accurate responses and quick routing to the right support option when a request is beyond the chatbot's scope.

Finally, the study's satisfaction measures and open feedback logic support a recommendation for a structured AI specific feedback and improvement cycle. OmniBSIC Bank should introduce short post interaction feedback prompts for AI channels and review the results on a fixed schedule to identify recurring pain points linked to the measured constructs, such as slow responses, unclear guidance, or unresolved issues. The feedback should be reviewed jointly by customer service and IT so that improvements translate into measurable changes in AI feature performance and AI tool quality scores over time.

5.4 IMPLICATIONS FOR PRACTICE AND POLICY

The findings carry important implications for policy within the banking sector, particularly as regulators and financial institutions continue to navigate the integration of artificial intelligence into service delivery. Policymakers should consider establishing clear guidelines that ensure transparency in AI operations, especially in areas related to data usage, personalization and automated decision making. The strong reliance on AI tools such as chatbots and fraud detection systems in this study highlights the need for policies that standardize the performance, reliability and security of AI platforms across the banking industry. Regulatory bodies may also need to develop compliance frameworks that require regular audits of AI systems, ensuring they remain fair, accessible and capable of safeguarding customer trust. Given that customer satisfaction is strongly tied to perceptions of accuracy, speed and reliability, policy measures that promote technological accountability and responsible AI practices would support customer protection and enhance consumer confidence in AI enabled financial services.

The study also opens pathways for future research, particularly in examining deeper customer behavioral responses to AI systems as they evolve. Future studies could adopt a mixed methods approach to explore qualitative insights into how customers interpret AI interactions, especially in areas where satisfaction is moderate, such as personalization and proactive financial guidance. Longitudinal studies may also help assess changes in satisfaction as AI systems become more adaptive and integrated into banking operations. Comparative research across multiple financial institutions would further strengthen generalizability and offer broader perspectives on AI adoption trends. Additionally, researchers should explore the role of digital literacy in shaping customer engagement with AI services, as this factor may influence satisfaction levels and the perceived value of AI tools. By addressing these areas, future research can provide a more holistic understanding of how AI continues to transform customer service experiences within the financial sector.

5.5 LIMITATIONS OF THE STUDY AND FUTURE RESEARCH DIRECTIONS

The study has limitations that shape how the findings are interpreted and applied. First, the study relies on a structured questionnaire, so measurement error and response bias remain possible. Some respondents may interpret items differently or provide socially desirable answers, particularly where questions refer to service quality and satisfaction. The study therefore captures reported perceptions rather than directly observed service performance. Second, the study focuses on customers of OmniBSIC Bank, so the findings are context specific and may not generalise to other banks that differ in customer profiles, digital maturity, or the type and coverage of AI enabled service channels. Third, customer access and willingness to participate limit representativeness. Customers who were rushed, unavailable, or less comfortable with digital services may be under represented, and this may affect the stability of estimates for AI tool usage and satisfaction. Fourth, the study uses a cross sectional design, which limits causal inference because it measures exposure and satisfaction at one point in time. Finally, some participants may not fully understand what qualifies as AI, which can lead to misclassification of tool usage and more superficial evaluations of AI features.

Future research can address these limitations directly. Studies can strengthen measurement quality by pretesting items more extensively, using clearer screening prompts and examples to confirm that respondents are rating AI enabled services rather than general digital banking tools. Research can also extend generalisability by replicating the study across multiple banks and regions in Ghana, using comparable instruments to test whether the observed relationships hold under different service models and customer demographics. To reduce participation and representativeness constraints, future surveys can use a wider set of customer contact points and combine in branch recruitment with verified digital channels so that customers who mainly use mobile or remote services are adequately captured. Longitudinal designs can also be introduced to track satisfaction over time after changes in AI service features, which supports stronger inference about direction of influence. Mixed methods studies, such as follow up interviews with selected respondents, can further explain why certain AI features drive satisfaction and clarify the practical reasons behind low ratings or non use among specific customer groups.

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APPENDIX

RESEARCH QUESTIONNAIRE

INTRODUCTION

Dear Valued OmniBSIC Bank Customer,

I am a master's student at UniMAC-IJ. I am currently undertaking a research study titled "**Examining the Impact of Artificial Intelligence on Customer Satisfaction in the Banking Industry.**" The purpose of this study is to better understand how the Artificial Intelligence (AI) tools used by OmniBSIC Bank influence your satisfaction as a customer. Your insights are invaluable as they will help us examine the types of AI tools you have experienced, the relationship between AI-powered customer service tools and your perceived satisfaction and identify which specific AI features you find most influential.

This survey will take approximately 10-15 minutes to complete. Your participation is completely voluntary, and all your responses will be kept strictly confidential and used solely for academic purposes. Your name will not be associated with your answers, and the data collected will be analyzed in an aggregated form.

Section A: Demographics

1. What is your age?

[ ] Under 18 years
[ ] 18-24 years
[ ] 25-34
[ ] 35-44
[ ] 45-54
[ ] 55-64
[ ] 65 or older

2. What is your gender?

[ ] Male
[ ] Female
[ ] Prefer not to say
[ ] Other (please specify): ______________________________

3. What is your highest level of education completed?

[ ] Primary School
[ ] Junior High School (JHS) / Middle School
[ ] Senior High School (SHS) / Secondary School

[ ] Vocational/Technical Training
[ ] Diploma/Higher National Diploma (HND)
[ ] Bachelor's Degree
[ ] Master's Degree
[ ] Doctorate (PhD)
[ ] Other (please specify): ______________________________

4. How many years have you been a customer of OmniBSIC Bank?

[ ] 1-3 years
[ ] 4-6 years
[ ] 7-10 years
[ ] More than 10 years

Section B: AI Tool Usage (Type Identification)

5. Please indicate which types of AI-powered customer service tools you have used at OmniBSIC Bank in the past 12 months. (Select all that apply)

[ ] AI Chatbot on websites or mobile app

[ ] Virtual Assistant (e.g., voice-activated assistant)

[ ] Automated phone system with AI features (e.g., voice recognition, automated routing)

[ ] Personalized product recommendations (e.g., for products or services)

[ ] AI-powered fraud detection alerts

[ ] AI-driven product recommendations or proactive financial guidance.

[ ] I have not used any AI-powered customer service tools. (*Filter: If selected, proceed directly to Section E.*)

[ ] Other (please specify): ____________________________

Section C: AI Feature Performance

This section addresses the individual effects of key features

Instruction: Using the scale below, please indicate your level of agreement regarding the performance of the AI customer service tools you have used at OmniBSIC Bank.

Scale:	**1 = Strongly Disagree**	**2 = Disagree**	**3 = Neutral**	**4 = Agree**	**5 = Strongly Agree**
Question	**1**	**2**	**3**	**4**	**5**
Is the user interface of the AI system intuitive and easy to navigate?					
Are you satisfied with the speed of response provided by the AI system when you contact customer service?					
Does the personalization feature of the AI system effectively tailor responses to meet your unique banking needs?					
Do the embedded security features of the AI tool instill a strong sense of trust and confidence in using the digital service?					

Section D: AI Tool Quality and Usage

Instruction: Using the scale below, please indicate your level of agreement regarding the overall quality and effectiveness of AI customer service tools at OmniBSIC Bank.

Scale:	**1 = Strongly Disagree**	**2 = Disagree**	**3 = Neutral**	**4 = Agree**	**5 = Strongly Agree**
Question	**1**	**2**	**3**	**4**	**5**
Does the AI-powered customer service tool address your banking inquiries with accuracy?					
Does the availability of the AI tool 24/7 significantly improve your ability to access banking services at any time?					
Does the integration of AI technology enhance the overall efficiency of resolving your banking transactions?					
Is the information provided by the AI tools clear, precise, and reliable?					
Does the automated system consistently reduce the waiting time					

Scale:	1 = Strongly Disagree	2 = Disagree	3 = Neutral	4 = Agree	5 = Strongly Agree
compared to traditional customer service methods?					
Does the quality of automated responses from the AI service meet your expectations for professional customer service?					

Section E: Overall Customer Satisfaction

Instruction: Using the scale below, please rate your satisfaction with the following aspects of OmniBSIC Bank's services.

Scale:	1 = Very Dissatisfied	2 = Dissatisfied	3 = Neutral	4 = Satisfied	5 = Very Satisfied
Question	**1**	**2**	**3**	**4**	**5**
Are you generally satisfied with the overall banking services provided by OmniBSIC Bank?					
Are you satisfied with the professionalism of OmniBSIC					

Scale:	**1 = Very Dissatisfied**	**2 = Dissatisfied**	**3 = Neutral**	**4 = Satisfied**	**5 = Very Satisfied**
Bank's human customer service staff?					
Do you believe your overall satisfaction with the bank's services has increased as a result of using AI-powered customer service tools?					
How likely are you to recommend OmniBSIC Bank to friends or family?					

Thank you for your time.