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Customer Perceptions of AI Chatbots as Corporate Communication Channels in the Kenyan Banking Industry

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ABSTRACT

Despite the increasing integration of artificial intelligence into financial services globally, and Kenya's proven leadership in mobile banking innovation, limited scholarly attention has been directed toward understanding how customers of Kenyan banks perceive AI chatbots as corporate communication channels, specifically whether they communicate effectively and earn customer trust, rather than as operational tools.This study sought to address that gap by analyzing levels of trust, satisfaction, and frustration among customers who have interacted with chatbot systems and to develop evidence-based recommendations for improving customer experience and strengthening organisational communication through AI-driven channels.A quantitative, cross-sectional research design was employed. Data was collected through a structured self-administered questionnaire distributed to respondents via WhatsApp and a final sample of 96 respondents was analysed.

Findings indicate that customers generally evaluated chatbots as useful and reasonably efficient for handling routine banking queries. However, these perceptions were primarily shaped by whether customers trusted the chatbot and by the quality of their direct experience using it rather than demographic characteristics. Specifically, trust in the information provided by chatbots, quality and speed of responses, and the ease of escalating to human assistance. Demographic variables such as age and level of education played a comparatively limited role, a finding consistent with the sample's predominantly young and highly educated profile. Taken together, the results suggest that customer evaluations of chatbots depend less on who the customers are and more on what the chatbots actually do in practice, and how they do it.These findings carry important implications for Kenyan banks seeking to deploy AI chatbots as communication channels. While customers broadly acknowledge the convenience and accessibility that chatbots offer, they remain cautious due to concerns around trust, data security, and the limited capacity of current chatbot systems to handle complex or sensitive interactions. Banks should therefore invest in transparent data governance frameworks and position chatbots and human agents as complementary resources, ensuring that seamless human escalation remains available as a foundation of the customer experience.

Keywords : AI chatbots, customer perceptions, corporate communication, Kenyan banking, trust, customer experience, human-chatbot interaction

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Abbreviations

AI	Artificial Intelligence
AIML	Artificial Intelligence Markup Language
ANOVA	Analysis of Variance
API	Application Programming Interface
CA	Communications Authority of Kenya
CRM	Customer Relationship Management
DPA	Data Protection Act
ECT	Expectation-Confirmation Theory
e-SQ	Electronic Service Quality
EVA	Equity Virtual Assistant
GDPR	General Data Protection Regulation
HSD	Honestly Significant Difference
IBM	International Business Machines
IS	Information Systems
M-Pesa	Mobile Pesa (Mobile Money)
NLP	Natural Language Processing
PEOU	Perceived Ease of Use
PU	Perceived Usefulness
SERVQUAL	Service Quality Model
SPSS	Statistical Package for the Social Sciences

TAM	Technology Acceptance Model
UBA	United Bank for Africa
XML	Extensible Markup Language

INTRODUCTION

The rapid development of artificial intelligence (AI) technologies has significantly reshaped organizational communication practices across industries. Among these technologies, AI-powered chatbots have emerged as notable corporate communication tools, enabling organizations to interact with stakeholders in real time through natural language processing. Some of the functions Chatbots are increasingly used for are: to handle customer inquiries, provide information, and support service delivery, therefore transforming how organizations manage communication efficiency, responsiveness, and relational engagement.

In the financial services sector, banks have been at the frontline of chatbot adoption due to growing customer expectations for instant, personalised, and round-the-clock communication. Chatbots are positioned as cost-effective solutions (Graham et al., 2025) that reduce operational load while improving customer experience (Hoyer et al., 2020, as cited in Graham et al., 2025). From a corporate communications perspective, chatbots are more than just technical service tools; they serve as organizational representatives that mediate relationships between banks and customers. As a result, how customers perceive these AI-mediated interactions, particularly in terms of trust and communication effectiveness, is a critical concern, especially in a sensitive sector like banking (Kaakandikar et al., 2025).

In Kenya, the importance of AI-driven communication in banking is amplified by the country's advanced digital financial ecosystem. Kenya is widely recognized for its high levels of mobile banking penetration, fintech innovation, and digitally engaged population (Kodongo, 2024) Banks in advanced markets increasingly use AI chatbots across mobile applications, websites and social media channels to enhance customer engagement, a move that is also emerging in Kenya's banking sector.

Despite growing global literature on AI chatbots, much of this research is in Western or Asian settings and often takes a technology adoption or information systems perspective, with limited attention to customer perception, communication and the realities of emerging markets.

In this context, examining how customers perceive AI chatbots as corporate communication channels in the Kenyan banking industry is both timely and necessary.

1.0 Background of the Study

Kenya has placed itself as a pioneer in digital finance innovation, leveraging mobile banking platforms to achieve unparalleled financial inclusion. As artificial intelligence is emerging as a strategic enabler of customer engagement, operational efficiency, and competitive differentiation, conversational AI agents, specifically chatbots, have come into view as a prominent application in banking customer service.

Local bank initiatives such as Absa Bank Kenya's 'Abby' and Equity Bank's 'EVA' exhibit practical efforts to integrate AI chatbot technologies across widely used platforms like WhatsApp and social media, expanding service reach and accessibility.

In this setting, chatbots are not only tools for efficiency but also serve as corporate communication channels (Graham et al., 2025) where culture, digital literacy levels, and socio-economic status shape customer expectations for clarity, responsiveness, and trust.

However, the adoption of AI chatbots as corporate communication channels presents a contradiction. While banks implement these technologies to reduce costs and enhance service delivery, customer trust and acceptance remain uncertain.

Emerging markets also introduce different challenges and opportunities that remain under-researched. African banks face unique constraints, including fragmented data infrastructure, limited local languages support in chatbot systems (The Mobile Economy Africa 2025, 2025), and lower digital literacy among customers, which differ from challenges in developed markets.

1.1 Problem Statement

Despite the increasing use of AI chatbots in banking globally and Kenya's demonstrated leadership in mobile banking innovation, there is a knowledge gap in understanding how customers of Kenyan banks perceive AI chatbots, specifically as corporate communication channels, in terms of communication effectiveness and user trust, rather than as operational tools.

Existing research focuses on developed economies, rendering the findings inadequate for the Kenyan banking context, which presents distinct cultural, technological, and regulatory dynamics. Studies from Africa e.g Nigeria exist, however, Kenya-specific research remains scarce. This geographic gap is crucial because communication effectiveness is culturally and contextually set. Findings from Western African markets may not translate to Kenyan customer expectations, communication preferences, or trust formation mechanisms.

1.2 Research Objectives

- To examine customer perceptions of AI chatbots in Kenya's banking industry.
- To assess trust, satisfaction, frustration, perceived usefulness, and brand perception among customers using AI chatbots.
- To provide recommendations for improving customer experience and strengthening organizational communication through AI-driven channels in the banking industry.

1.3 Research Questions

Main Question

- How do Kenyan customers perceive AI-driven communication channels, specifically chatbots, in banking services?

Sub -Questions

- To what extent do customers trust AI-generated corporate messages and interactions?
- How do customers perceive the effectiveness of AI-driven communication channels compared with traditional human interaction for simple queries?
- What challenges or frustrations do customers encounter when engaging with AI-driven communication channels?
- What improvements do customers suggest for enhancing AI-based communication?

1.4 Justification and Significance of the Study

Much of the current research on AI chatbots emphasizes system performance and efficiency, such as dialogue and relationship-building. This limits understanding of how chatbot interactions function as communicative encounters rather than purely transactional exchanges.

The findings of this study are expected to contribute to multiple stakeholders. For academic researchers, the study extends corporate and digital communication research by objectively examining AI chatbots through the lenses of communication effectiveness and trust in an emerging market context. It also provides a foundation for future research on AI-mediated organizational communication in Africa, contributing to the growing number of international business research addressing non-Western markets.

For banking practitioners, the study offers insights into how customers perceive AI chatbot communication, identifying factors that enhance or undermine trust and effective dialogue. These insights can inform the strategic design and deployment of chatbots to improve customer engagement and institutional credibility.

Kenya's banking sector stands at a critical juncture. The sector has demonstrated both technological readiness and customer demand for digital services, yet customer trust in AI remains substantially below technology adoption rates globally. The window to shape customer perceptions and establish positive communication norms around AI chatbots is narrow; as systems become increasingly integrated into banking operations, shaping customer expectations becomes progressively more difficult. Research conducted now will have greater policy and practice relevance than research conducted after widespread chatbot deployment.

Additionally, findings can contribute to broader financial inclusion policy by demonstrating that technology adoption alone is insufficient; strategic communication and trust-building must accompany technological deployment.

1.5 Definition of Key Terms

Customer Perceptions

Customer perceptions are customers' views of products or services based on their conclusions. The conclusions are derived from experience and expectations (T R & S, 2017). In AI contexts, perceptions encompass beliefs about the technology's usefulness, ease of use and trustworthiness.

In this research, *Customer perceptions* refer to how Kenyan banking customers subjectively evaluate AI chatbots as communication agents and channels.

Artificial Intelligence (AI)

Artificial Intelligence is the ability of a machine to perform functions associated with human intelligence, such as perceiving, reasoning, learning, problem-solving, and decision-making (Rai et al. (2019), as cited in Collins et al., 2021).

In this study, *AI* is used as an umbrella term, but the focus is on AI-powered chatbots deployed by Kenyan banks.

AI Chatbots

AI Chatbots are AI-driven softwares designed to simulate human conversation and provide support to customers in real-time (Kaakandikar et al., 2025). They use natural language processing (NLP) and other AI technologies to interpret user queries.
In this research, *AI chatbots* refer specifically to AI-powered customer-facing conversational agents implemented by Kenyan commercial banks, accessed via mobile apps, websites, and messaging or social media platforms. The study treats them as corporate communication channels, enabling institutional interaction.

Corporate Communication

Corporate communication entails management of all means of communications with stakeholder groups that the organization is dependent on, with the overall purpose of building and maintaining a favourable reputation(Cornelissen, 2004). It consists of both formal and mediated communication channels.

In this study, *Corporate communication* describes banks' planned and managed communication with customers, including support, information and relationship-oriented interaction. AI chatbots are seen as emerging corporate communication channels because they deliver institutional messages and represent the banks’ voices in customer interactions.The study examines whether these chatbots fulfill communication functions traditionally associated with human agents.

Channels (communication channels)

Communication channels are the methods and the specific tools used in the communication process (eCampusOntario Pressbooks, n.d.) such as telephone, email, websites, mobile applications, and conversational interfaces.

In this research, *channels* refer to customer-facing communication channels used by Kenyan banks, including AI chatbots, SMS, mobile and online banking interfaces, social media, through which banks conduct corporate communication with their retail customers.

2.0 Literature Review

2.1 Theoretical Foundation

2.1.1 Corporate communication as a discipline

Corporate communication has evolved over the years from different disciplines and functions, such as public relations (Cornelissen, 2004), into a management function aligning all organisational communications and interactions with groups upon which the company is dependent, to support corporate objectives, identity, and reputation (Van Riel, as cited in Cornelissen, 2004). The discipline underscores credibility, consistency and clarity in how organizations present themselves across various communication channels (Harcourt Whyte, 2025).

Historically, corporate communication mainly focused on information dissemination through formal channels such as press releases, annual reports, and media relations; however, recent studies position it as a strategic function responsible for managing stakeholder relationships and maintaining corporate reputation (Argenti, 2023; Cornelissen, 2004). Organizations do not transmit information only; they cultivate trust, manage reputation, and shape corporate identity through deliberate communication efforts.

Communication channels are, therefore, strategic instruments through which organizations shape stakeholder perceptions and reinforce legitimacy. The choice of channel influences how stakeholders interpret messages, assess responsiveness, and gauge institutional credibility.

In service industries like banking, where products are invisible and difficult for customers to rate, interactions become important in shaping customer experience and confidence (GRÖNROOS, 2015).

Within this theoretical framework, corporate communication stretches beyond traditional interactions driven by humans to include digital platforms. As technological systems become part of organizations' communication infrastructure, understanding how these systems function as extensions of corporate voice becomes more and more crucial.

2.1.2 Technology-Mediated Communication

Digitalisation has transformed a large share of corporate communication from physical to technology-mediated platforms, including websites, mobile applications, social media, and increasingly conversational agents such as chatbots.AI chatbots represent an important development within this transformation, functioning as interactive digital agents that simulate conversational engagement (Adam et al., 2021) while remaining organization-controlled systems.

Technology-mediated channels differ in social presence and richness (Kojima et al., 2021), reducing physical cues, often operating through automated processes. While these aspects increase efficiency and accessibility, they shape how messages are interpreted, relationships developed, and trust is built or broken. They also redefine stakeholder expectations. Customers now expect instant responses, 24-hour service, personalised engagement, and seamless navigation across platforms.

In most scenarios, technological interfaces are the first touchpoints between customers and organizations. These interfaces influence their perceptions. A poorly designed digital communication channel can negatively affect how customers perceive the organization.

Technology-mediated communication also introduces new challenges, e.g., lack of human warmth, reduced emotional cues, and concerns about security and reliability may affect stakeholder trust (Adam et al., 2021; Bitner et al., 2000). In trust-dependent industries such as banking, the integration of automated communication systems must therefore be carefully looked into from a perception standpoint.

2.1.3 Customer - Organization Interaction

The two-way symmetrical model of communication stresses dialogue over one-way messaging (Excellence Theory, 2013). The interaction between customers and organizations is no longer a one-way street. It is increasingly viewed as a reciprocal, two-way process in which stakeholders actively interpret, evaluate, and respond to organizational communication, with effective stakeholder engagement requiring both one-way information flows and two-way communication that adds mutuality and reciprocity to organizational interaction (Kujala et al., 2022). This means that the effectiveness of a communication channel cannot be measured simply by whether a message was sent and received. How customers perceive and experience that interaction is equally important.

Research shows that customer perception is a key driver of outcomes like trust, satisfaction, and loyalty. In digital settings, trust is shaped by dynamics such as transparency, and ethical considerations around data privacy, and businesses must establish trust through virtual interactions that prioritize clear communication and secure transactions (Yum & Kim, 2024).

When customers interact with a digital interface, they are not passive recipients of information, they are evaluating it. Research on e-banking shows that factors such as interface design, reliability, responsiveness, trust, and personalization all have a notable positive influence on customer satisfaction and loyalty in digital services (Al Firdaus & Rachmawati, 2024). These evaluative judgments determine whether a customer sees a channel as credible and worth engaging with.Customers interacting with the digital systems must believe that the communication channel accurately represents the institution and keeps their information safe. When interaction occurs through automated systems rather than human agents, the dynamics of relational evaluation shift. The communication interface itself becomes the representation of the organization in that moment of interaction.

Thus, AI chatbots hold a distinctive position within customer-organization communication. They simulate conversations, provide details, and guide service processes, operating through programmed algorithms rather than human agency. Consequently, customer perceptions of trust, ease of interaction, and satisfaction become important factors (Adam et al., 2021) in evaluating chatbots as corporate communication channels.

2.1.4 Theories and models

This study draws upon three theories and models. The Technology Acceptance Model (TAM), the Expectation-Confirmation Theory (ECT), and the Service Quality Model (SERVQUAL).

These theories together explain the full arc of the customer experience, from adoption decisions, through experiential evaluation, to quality judgments. TAM addresses the cognitive precursors that drive a customer's decision to engage with an AI chatbot, ECT captures how expectations versus actual experience shape satisfaction and SERVQUAL provides a structured lens through which the quality of AI-mediated banking communication can be evaluated.

In addition, given that this study lies within the Kenyan banking industry, a context marked by rapid digital transformation, evolving customer expectations, and increased sensitivity to financial data security, the concept of trust is integrated as a critical driver within the TAM discussion. As expounded in Section 2.1.4.1, trust functions as a prerequisite for perceived usefulness and perceived ease of use, and is therefore crucial for an in-depth understanding of AI chatbot adoption in this context.

2.1.4.1 The Technology Acceptance Model (TAM)

The Technology Acceptance Model was originally suggested by Fred D. Davis in his doctoral dissertation and later published in a historic article. Davis aimed to explain the drivers of technology acceptance or rejection. TAM suggests that two primary cognitive attitudes direct an individual's intention to use a new technology: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU).

Perceived Usefulness is defined as the extent to which a person believes that using a system would improve their job performance, and a user believes in a positive use-performance relationship when a system has high perceived usefulness (Davis, 1989). In the context of the use of AI chatbots in banking, Perceived Usefulness represents the degree to which customers believe that interacting with an AI chatbot will improve the speed, convenience, or quality of their banking experience.

On the contrary, Perceived Ease of Use refers to the degree to which a person believes that using a particular system will be effortless(Davis, 1989). Customers who find a chatbot easy to use than other alternatives are more likely to develop a positive attitude towards it and, as a result, continue to use it.

TAM further indicates that both Perceived Usefulness and Perceived Ease Of Use influence decisions to use a technology(Davis, 1989).

TAM has been widely used in studies of banking and financial technology. For example,(Pikkarainen et al., 2004) applied TAM to online banking acceptance and adoption and identified Perceived Usefulness was one of the most influential factors of consumer acceptance.

In Kenya, mobile banking platforms such as M-Pesa have already created a culture of digital financial interaction, therefore TAM offers a very relevant framework. Customers who have earlier positive experiences with digital financial tools may display more positive default perceptions of usefulness and ease of use when interacting with AI chatbots. In contrast, customers with limited digital literacy or prior negative experiences with digital solutions may be resistant, highlighting the role that personal attitudes play in shaping chatbot adoption.

While TAM provides an in-depth framework for understanding technology adoption, experts argue that in high-risk environments, especially those involving sensitive personal data, trust is a critical prior condition to both Perceived Usefulness and Perceived Ease of Use(Gefen et al., 2003).In low-risk technology settings, users may evaluate a system primarily on its functional quality. However, when financial transactions, account data, or personal identities are involved, as is the case in banking, customers must trust the system first before they can willingly engage with it or positively evaluate it.

Mayer, Davis and Schoorman (1995) define trust as ‘’the willingness of a party (trustor) to be vulnerable to the actions of another party (trustee) based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party" (Söllner et al., 2010). This definition depicts the inherent vulnerability customers face when sharing financial information with automated systems such as AI chatbots, whose decision-making processes are often non-transparent.

McKnight and Chervany (2002) further differentiate between dispositional trust and institutional trust. ''…dispositional trust means one trusts in others generally, institutional trust means one trusts the situation or structures ". In the Kenyan banking industry, customers' trust in a bank's AI chatbot is therefore likely influenced by their existing trust in the bank as an institution, as well as their general confidence in the security of digital financial systems.

Thus, this study extends the traditional TAM model to incorporate trust as an antecedent variable, as illustrated in Figure 1 below. It proposes that customer trust in AI chatbots directly and positively influences both Perceived Usefulness and Perceived Ease of Use, which in turn shape Behavioural Intention to Use. This extension recognizes that in the Kenyan banking context, the adoption of AI chatbots cannot be fully comprehended without accounting for the trust perception that either enables or limits engagement with these systems.

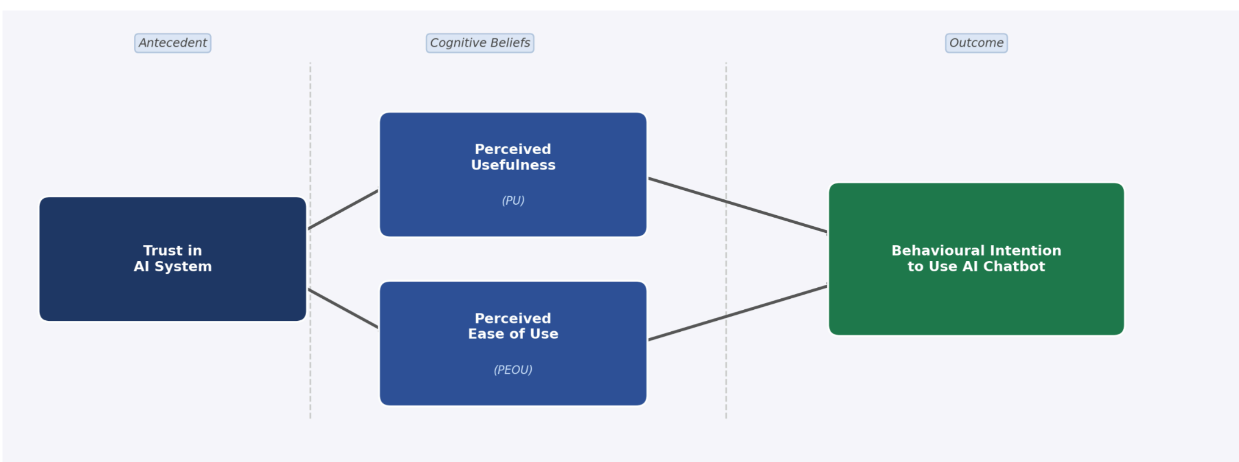

Figure 1: Extended TAM Model with Trust Antecedent (Own Illustration)

2.1.4.2 Expectation-Confirmation Theory (ECT)

Expectation-Confirmation Theory was originally developed by Richard L. Oliver to expound consumer satisfaction as a post-purchase occurrence.

The theory suggests that satisfaction is determined by the level to which a customer's experience confirms or disconfirms their expectations before exposure to the product. When a product or service performs better than expected, positive disconfirmation occurs, leading to satisfaction. When the outcome is worse than expected, negative disconfirmation occurs, leading to dissatisfaction. When performance matches expectations exactly, simple confirmation occurs (Oliver, 1980).

The theory was later adapted by (Bhattacherjee, 2001) within the scope of information systems continuance (the decision to continue using a technology) to develop Information Systems (IS) Continuance Model, which states that the intention to continue using a system is as a result of two variables: Satisfaction with the system which is influenced by the confirmation of expectations formed before use, and the perceived usefulness experienced from continued use.

This reformulation is especially significant for this study, as it shifts the focus from technology adoption as addressed by the Technology Acceptance Model (TAM) to customer engagement and retention.

TAM explains why a customer first chooses to engage with an AI chatbot, while ECT explains whether that initial choice is validated or abandoned over time. The interrelationship between these two models is relevant to the Kenyan banking industry, where customer retention on digital channels is a strategic priority for commercial banks seeking to reduce branch-based and call-centre interactions costs.

ECT is particularly relevant to the study of AI chatbots because prior experiences with human agents, marketing, and peer recommendations usually shape customer expectations. On their first interaction with a bank's AI chatbot, they have a pre-formed set of expectations on the speed, accuracy, helpfulness, and personalisation of the interaction. The degree to which the chatbot confirms these expectations will determine whether customers are satisfied and whether they choose to use the chatbot again.

In Kenya, the implementation of AI chatbots in banking is still emerging, and many customers are not familiar with such systems; therefore, expectation-confirmation dynamics are likely to be particularly important. Customers who use chatbots for the first time with high expectations, maybe expecting a human-like conversational experience, may experience sharp negative disconfirmation if the chatbot is perceived as impersonal. On the contrary, customers with moderate initial expectations may be amazed by the chatbot's efficiency, leading to positive disconfirmation and higher satisfaction.

2.1.4.3 Service Quality Model (SERVQUAL)

The SERVQUAL model was developed by Parasuraman, Zeithaml and Berry as a multiple-item scale for measuring customer perceptions of service quality in service and retailing organizations. The model is rooted in the premise that service quality is the difference between customers' perceptions and expectations of the services offered by an organization (Parasuraman et al., 1998).

While Parasuraman et al. (1985) originally identified ten service quality dimensions along which customers assess service quality, these were subsequently refined and consolidated into five dimensions in the 1988 SERVQUAL instrument through empirical scale development (Parasuraman et al., 1998)

The dimensions include :

Tangible, which refers to the physical facilities, equipment, and appearance of personnel. In the context of AI chatbots, tangibles translate to the visual design of the chatbot, and the overall aesthetic of the interaction environment.

Reliability, which is defined as the ability to perform the promised service dependably and accurately. In this study, reliability refers to the consistency and accuracy of the information provided by the AI chatbots.

Responsiveness covers the willingness to help customers and provide prompt service. In AI chatbot interactions, responsiveness is the speed with which the chatbot addresses customer queries, as well as its ability to escalate complex queries to human agents on time.

Assurance refers to the knowledge and courtesy of employees, and their ability to instill trust and confidence. In the context of this research, assurance is linked to the chatbot's ability to provide authoritative, accurate, and professional responses, therefore instilling confidence in the customer that their banking needs are being competently met.

Empathy is defined as the provision of caring, individualised attention to customers. This is possibly the toughest dimension for AI chatbots to fulfil, given the inherent limitations of natural language processing in replicating the warmth and contextual sensitivity of human interaction. Researchers have used the idea of anthropomorphism, which refers to the tendency to assign human traits, intentions, and emotions to non-human entities (Epley et al., 2007), to explain how anthropomorphizing technological agents such as AI chatbots can compensate for this limitation. When AI chatbots are designed with human-like conversational cues, such as personalised greetings, natural language responses, and empathetic phrasing, customers are more likely to perceive them as socially present and emotionally responsive, thereby positively influencing their evaluations of empathy (Sidlauskiene et al., 2023). In the Kenyan banking industry, customer communication has traditionally been relationship-driven, therefore the degree to which customers perceive AI chatbots as empathetic is a particularly important determinant of perceived service quality.

SERVQUAL was initially developed for face-to-face service encounters, but scholars have largely adapted it to digital and online service environments, bringing about e-service quality (e-SQ). In a survey on Webmasters for Fortune 1000 companies, Liu and Arnett (2000) measured and found five factors to be key to e-service quality success with consumers:-

Quality of information, which consists of presentation of relevant, accurate, timely, customized and complete information.

Service which involves quick response, assurance, empathy and follow-up.

System use includes security, correct transaction, customer control on transaction,order-tracking facility, and privacy.

Playfulness perceived by consumers, which is determined by customers' sense of enjoyment, interactivity, attractive features, and enabling customer concentration.

Design of the system/interface involves organized hyperlinks, customized search functions, speed of access, and ease of correcting errors.

Within this theoretical framework, SERVQUAL serves as the evaluative climax, providing a structured, multifaceted lens through which the quality of AI chatbots interactions is comprehensively assessed.

2.2 Synthesis and Conceptual Framework

The three theories reviewed in this chapter, the Technology Acceptance Model (TAM) extended with Trust, Expectation-Confirmation Theory (ECT), and Service Quality Model (SERVQUAL), are progressively and logically connected as shown in Figure 2 below.

In the pre-adoption phase, TAM extended by trust theory explains the cognitive and evaluative processes that determine if a customer is willing to engage with a bank's AI chatbot. Trust in the AI system and in the banking institution conditions the customer's assessments of perceived usefulness and perceived ease of use, which together shape their behavioral intention to use the chatbot.

In the experience phase, ECT captures the evaluation process that unfolds during and immediately after the chatbot interaction. Customers compare the actual performance of the chatbot against their pre-formed expectations, and the degree of confirmation or disconfirmation determines their level of satisfaction. Satisfied customers are more likely to use the chatbot again in the future, while dissatisfied customers may go back to using traditional banking channels.

In the evaluation phase, SERVQUAL provides the multi-dimensional quality assessment framework through which customers express their perceptions of the chatbot's service quality. The five e-service quality (e-SQ) factors of quality of information, service, system use, playfulness perceived by consumers and design of the system/interface employ the abstract concept of "quality" into a measurable, researchable construct that can be systematically analysed.

This integrated framework provides a theoretically grounded, practical, and contextually relevant foundation for the research of customer perceptions of AI chatbots as corporate communication channels in the Kenyan banking industry.

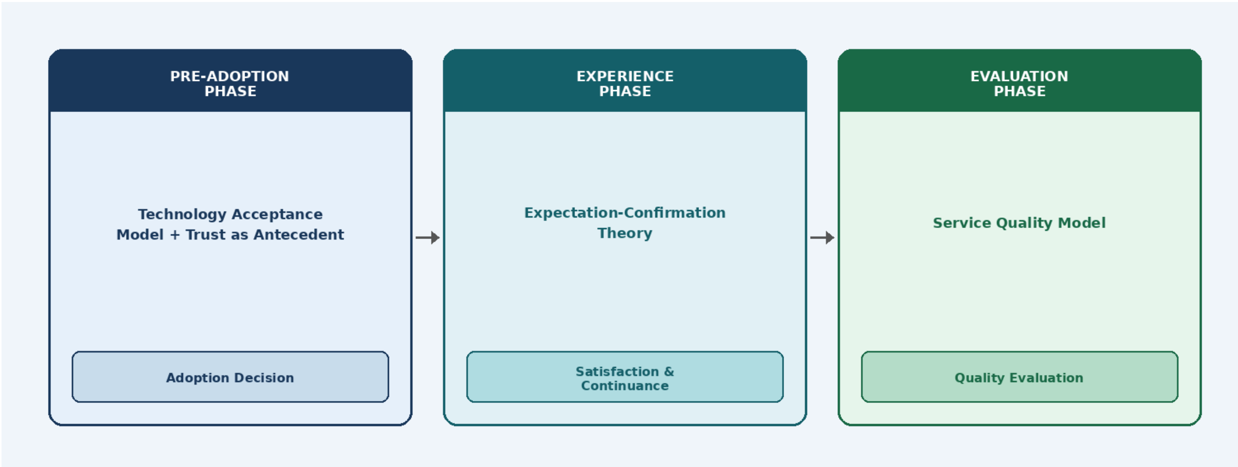

Figure 2: Conceptual Framework (Own Illustration)

2.3 AI Chatbots: Characteristics and Communication Functions

Chatbots have emerged as important actors in digital communication, transforming how organizations and individuals interact across different industries (Afgiansyah et al., 2026).

This section examines recent developments in computer-mediated communication, with particular focus on the role of AI within communicative processes. It explores how AI chatbots engage with humans and the extent to which computer-mediated communication is shifting toward a more active role as AI systems increasingly interact directly with users.

2.3.1 Communicative Capabilities of Rule-Based Chatbots versus AI-Powered Chatbots

Rule-based chatbots function by matching user inputs to a predefined repository of question-answer pairs. This approach was formalised with the release of AIML, an XML-based framework for chatbot development, in 2001 (Maher et al., 2020).

Despite their effectiveness in handling simple, predictable tasks, rule-based chatbots fell short in contexts requiring adaptive or context-sensitive communication with customers (Falkner et al., 2025). The conversational limitations of the systems are clear when examining their inability to adapt to new user inputs or understand contextual differences. These systems cannot generate new responses because they are confined to pattern matching against predefined repositories.

On the other hand, AI-powered chatbots demonstrate significantly expanded communicative capabilities. The development of Natural language processing (NLP) and machine learning has enabled the chatbots to move beyond scripted responses, allowing them to interpret customer intent and engage in communication that closely mirrors human dialogue(Falkner et al., 2025). These chatbots, also known as generative model chatbots, do not use a fixed response repository; they use deep learning algorithms to independently generate replies, making them more advanced (Maher et al., 2020). They outdo the limitations of rule-based systems by adapting to user preferences, managing multi-turn conversations, and simulating empathetic communication, positioning them as fundamentally different communicative actors.

They can learn user preferences, sustain multi-turn conversations, and simulate forms of social engagement that appear empathetic(Afgiansyah et al., 2026). This fundamental difference in communicative capacity positions AI-powered chatbots as qualitatively different communication actors compared to their rule-based predecessors.

2.3.2 Communication Functions

AI chatbots are supported by a complex technological infrastructure that enables advanced communicative functioning. Neural network-based deep learning models strengthen language understanding and response prediction, while dialogue management systems further ensure contextual coherence across multi-turn interactions (Falkner et al., 2025). Together, these features position AI chatbots as active agents in dialogue that shape outcomes, rather than passive response systems.

An important communicative function distinguishing advanced AI chatbots is their ability to regulate tone and respond to emotional content. Sentiment analysis allows chatbots to recognise emotional cues behind user messages and adapt their tone appropriately (Falkner et al., 2025). This ability helps create a more empathetic and human-like interaction, which strengthens user satisfaction and trust. It also represents a significant difference from rule-based systems' impersonal responses. This communicative function operates at the practical level, recognizing that effective communication goes beyond the exchange of information and requires sensitivity to the emotional dimensions of human interaction.

Integration with Customer Relationship Management (CRM) platforms and enterprise databases extends the communicative capacity of AI chatbots by providing access to customer histories, preferences, and transactional data, enabling personalised interactions and recommendations, real-time service updates, and context-sensitive support. The result is a more engaging and meaningful experience for the user (Falkner et al., 2025).

Application Programming Interface (API) connectivity and cloud-based infrastructure further support omnichannel deployment across websites, mobile apps, social media, and messaging platforms, ensuring consistent customer engagement regardless of channel. This unified presence across platforms represents a communicative function unavailable to human agents, who are necessarily localized to specific channels.

Shah and Devgun (2025) state that AI chatbots can hold several conversations at once, which no human agent can. The scalability also allows businesses to handle large volumes of customer enquiries efficiently, especially during high-demand periods such as product launches or promotional campaigns. Even at peak times, chatbots guarantee seamless and consistent service.

2.3.3 Chatbots versus Human Agents

Comparison between chatbots and human agents reveals fundamental differences in communicative capacity and operational characteristics. Chatbots are limited when human empathy and critical thinking are needed in complex problems (Shah & Devgun, 2025). This limitation is especially important to understand where chatbots occupy a special role within communication ecosystems.

However, chatbots offer clear advantages in other areas. AI-powered chatbots serve as active real-time communication tools, providing instant and consistent interaction across multiple digital platforms without the constraints of human availability. This continuous communicative presence reduces response times, enhances service convenience, and shapes customers' overall perception of service quality. Over time, such responsiveness fosters deeper user engagement, encourages return visits, and strengthens the relational dimension of the customer-organisation communication dynamic (Falkner et al., 2025).

2.4 Global Perspectives on Chatbots as Communication Channels in Banking

Chatbot adoption in banking greatly varies across global markets, reflecting differences in technological infrastructure, customer preferences, and regulatory environments. In the United Arab Emirates, empirical data from a survey on major banks indicates that over 70% of customers have utilized chatbots, with particularly high satisfaction levels among younger demographics(Barman et al., 2025). This penetration rate reinforces the openness of banking customers in the Middle East to using AI-powered chatbots.

In contrast, African banking markets demonstrate emerging but growing adoption patterns. A number of banks in Nigeria, e.g Zenith Bank, United Bank for Africa (UBA), and Stanbic IBTC Bank, have integrated AI-powered chatbots as extensions of financial services and operations. Research by Esuh and Joseph Umoette (2025) from Akwa Ibom State reveal that approximately 49% of customers from these banks utilized AI-chatbots for self-service transactions, with 59% of the customers reporting that chatbot interactions influenced their perception of the banks. These statistics indicate that while adoption in African markets lags behind, the direction shows growing customer acceptance.

In India, findings from Poornima and P V (2026) study reflect broader global trends in chatbot adoption within the banking sector. Customer satisfaction with chatbot services tends to be moderate to positive, with round-the-clock availability consistently emerging as the most valued feature irrespective of region. However, a common challenge across markets is the accuracy and depth of chatbot responses, especially when requests from customers become complex. The study also points out that satisfaction is driven more by service quality than by usage frequency, a pattern echoed in banking markets worldwide. This reinforces the growing agreement that as chatbot adoption expands globally, banks must prioritize improving response accuracy and personalizing interactions, to meet the diverse communication needs of their customers.

2.4.1 Multilingual and Cultural Communication Dimensions

The effectiveness of chatbot communication is deeply connected with linguistic capacity and cultural appropriateness.Customer trust in banking chatbots is weakened when chatbots feel impersonal, fail to understand local languages, and make occasional technical errors (Poornima & P V, 2026), highlighting the direct influence of linguistic capability on customer perception and adoption. The ability to serve customers in different languages remains a critical differentiator in global banking markets.

Modern chatbot architecture addresses linguistic diversity through advanced natural language processing capabilities. Natural Language Processing (NLP) algorithms allows banks to serve customers in their own language, helping them reach more and diverse people around the world(Udeh et al., 2024).In multicultural societies, language barriers have long made it difficult for many people to access banking services, as traditional call centers were often unable to handle multiple languages, leaving customers frustrated and excluded. Today's chatbots solve this problem by using AI to communicate in different languages, and can even switch between languages based on what the customer prefers (Olaolu et al., 2023). This ultimately leads to greater customer satisfaction and loyalty.

Specific implementations demonstrate the strategic importance of multilingual capabilities in diverse markets.HDFC Bank in India introduced Eva, an AI chatbot that understands and responds to customer questions in multiple languages. After its launch, customer engagement went up by 30% and response times dropped by 20%, showing how effective AI can be in improving banking services(Udeh et al., 2024).

The practical implications of multilingual support extend beyond simple translation.A customer in India, for example, can switch between English and Hindi receiving the same quality of service in both cases. This makes banking more accessible to people who were previously excluded due to language barriers, promoting financial inclusion and helping banks reach new customers who were previously inaccessible and serve existing ones better (Olaolu et al., 2023).

Beyond language translation, cultural contexts fundamentally shape how customers interact with and perceive chatbot communication. In multilingual markets like the UAE where language differences create different usage patterns, chatbots need to be designed with cultural sensitivity in mind. This means going beyond just language translation. Chatbots must also reflect how different groups of people prefer to communicate, the level of formality they expect, and how they relate to financial service providers (Barman et al., 2025).

Culture shapes how people prefer to interact with their bank.In communities where personal relationships and trust are central, replacing human interaction with automation is a delicate balance. While chatbots can be designed to detect emotions and respond with care, they cannot truly replicate the warmth and trust that comes from a real human connection. This is why deploying chatbots globally goes beyond language translation. It requires a deep understanding of cultural nuances(Olaolu et al., 2023).

2.5 AI Adoption in Kenya: Context and Sector Overview

Kenya's leadership in mobile money and fintech innovation represents a broader trend of rapid adoption of modern technologies and expansion of digital systems in Sub-Saharan Africa (World Bank Group, 2024;Kuyoro et al., 2025).This positions the country as a useful case for understanding how AI spreads and is used in emerging-market contexts.

When viewed more broadly, the banking sector has drawn a lot of interest from researchers and professionals, because financial services play a key role in the Kenyan economy and banks have been among the first to adopt AI-driven customer-facing tools, including chatbots and virtual assistants (Jemutai, 2025).

A key starting point for understanding AI adoption in Kenya is looking at the country's digital setup. The Communications Authority of Kenya (2024) reported that mobile SIM subscriptions reached 68.9 million by June 2024, representing a penetration rate of 133.7%, while mobile internet traffic rose by 140% between 2022 and 2023, outpacing most East African peers. Mobile money penetration, powered primarily by Safaricom's M-Pesa platform, had reached approximately 91% of Kenyans by mid-2025, according to the Communications Authority of Kenya (2025).

These numbers help explain AI adoption in Kenya. Having a strong mobile-based financial system creates the right conditions for more advanced digital services, like AI chatbots, to be deployed. This connects to what researchers in technology adoption call "leapfrogging" which suggests that developing countries can bypass outdated technologies and move directly to the latest innovations (Kuyoro et al., 2025).

The policy and regulatory environment is another important aspect to understanding AI adoption in Kenya. The government has shown commitment to digital growth through key plans like the National Digital Master Plan (2022–2032) and, more recently, the Kenya National Artificial

Intelligence Strategy (2025–2030), which was officially launched on 27 March 2025. The AI strategy aims to position Kenya as the regional hub for AI research, innovation, and commercialisation. The strategy identifies the financial services sector as an area with AI research activities focused on creating solutions tailored to the unique needs of the African context. This lends institutional legitimacy to bank-led AI deployments. The strategy also signals an intent to address regulatory gaps around data sovereignty, accountability, and inclusion (Ministry of Information, Communications and the Digital & Economy (MICDE), 2025), areas that carry direct implications for how AI chatbots are designed and governed as communication channels.

Alongside the AI Strategy, Kenya also has the Data Protection Act (DPA) of 2019, which is the main law that controls the processing, storage, and sharing of personal data, including by AI systems. The law requires organisations to get people's permission before collecting their data, use that data only for its intended purpose, and keep it secure. For banks using chatbots, compliance is not just a legal obligation but also about protecting their reputation.

In 2024, the financial services sector accounted for a disproportionate share of data privacy violations (KO Associates, 2025) and the Data Protection Act (DPA) has pushed banks to be more open about how they handle customer data and to communicate clearly with customers about how their information is processed, a requirement that intersects directly with the communicative functions of AI chatbots(Kisia, 2026).

Despite this regulatory progress, several researchers have warned that Kenya's AI governance framework remains at an early stage, with ongoing regulatory and institutional gaps (Mwangi Chege, 2024). More broadly, there are growing concerns around transparency, bias, and accountability in AI systems, particularly in high-stakes financial contexts. Notwithstanding these challenges, Kenyan banks have moved with vigour in adopting AI technologies. According to the (Central Bank of Kenya, 2023) banks have adopted AI and machine learning in several operational areas, including customer experience enhancement and fraud risk management.

In terms of tools that customers interact with directly, AI chatbots have become especially common. Equity Bank launched its chatbot EVA, in May 2022. Customers can access it through WhatsApp, Facebook Messenger, and Telegram. Absa Bank Kenya has its own chatbot called

Abby, available on WhatsApp around the clock, helping customers carry out a variety of self-service banking tasks. KCB Bank has Kaycee and has shown plans to integrate comprehensive solutions across customer contact channels including WhatsApp, social media, and its website (Jemutai, 2025).

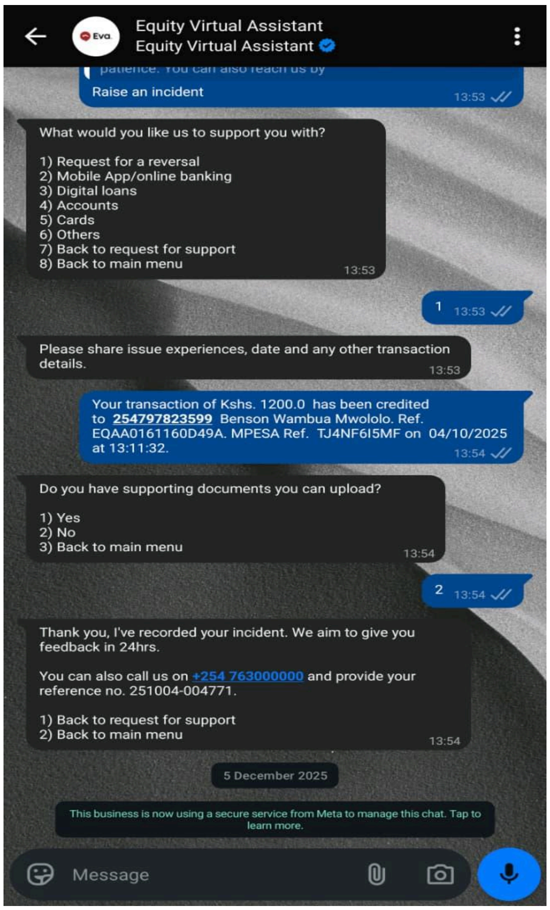

Figure 3: Screenshot of Equity Bank's EVA AI chatbot Interface on WhatsApp (Screenshot from a customer)

The operational rationale for the deployment and investment in AI chatbots is multifaceted and has been discussed by both industry professionals and researchers. From a cost-efficiency perspective, AI chatbots help banks reduce expenditure by handling large numbers of customer queries automatically, reducing the need to route every request to a human agent. From a service quality perspective, chatbots offer consistent service delivery promoting financial inclusion which is especially valuable in a country like Kenya, where many people live far from bank branches and have historically had limited access to financial services.

From a corporate communications perspective, chatbots can be understood as an emerging digital channel through which banks manage customer interactions and relationships at scale. However, while this scalability offers opportunities for enhanced customer engagement and operational efficiency, it also presents risks to brand perception. Research shows that when chatbot performance fails to meet user expectations customer satisfaction and trust can decline, potentially negatively affecting brand perception (Gu et al., 2024). As such, the effectiveness of chatbots as a corporate communication tool depends not only on their technological capabilities but also on their ability to deliver high-quality, human-like interactions that align with customer expectations.

There has been debate on positioning of AI chatbots within corporate communications theory and practice. Scholars have maintained that corporate communications is primarily concerned with managing relationships with stakeholders and protecting brand reputation (van Riel & Fombrun, 2007). It may be argued that chatbots serve three roles at once: functional tools that handle tasks, representatives of the brand, and relational agents. This three-in-one role does not fit neatly into traditional corporate communications models.

A study by (Nordheim et al., 2019) found that perceived expertise and responsiveness are important to users when deciding to trust a chatbot. Importantly, the study also found that brand perception independently shapes whether they trust a chatbot. This shows chatbots cannot be treated as purely technical products.They are also communication tools that carry reputational weight. This is especially important in Kenya, where customer trust in formal financial institutions has historically been cautious and contextually variable.

Despite the progress in AI adoption in Kenyan banking, literature also highlights a number of barriers and challenges. Infrastructure constraints, including poor or inconsistent connectivity in smaller towns and rural areas (Okello, 2023) which limits the accessibility for the population living there, even when banks want to serve them. Digital literacy is also uneven. While Kenya has a young population with a median age of 19 years, not everyone is comfortable with technology. Older customers and those with less formal education may find AI-powered interfaces difficult to use (Ministry of Information, Communications and the Digital & Economy (MICDE), 2025). Language may present a further barrier worth noting.Most bank chatbots in

Kenya tend to operate primarily in English, with limited Swahili support and almost no support for regional languages, potentially leaving out customers who are not fluent in English. On the regulatory side, Kenya's laws around data protection and AI are still developing and in some areas ambiguous, which creates uncertainty for banks trying to stay compliant (KO Associates, 2025).

2.6 Customer Perceptions of Chatbot-Mediated Communication

Trust is the most studied dimension of customer perception in chatbot research, and it matters especially in banking, where customers share sensitive financial information and expect high standards of institutional reliability.

A quantitative study across four major Indian banking chatbots found that trust in chatbots significantly predicted more positive attitudes, intentions to continue use of the chatbots and higher level of satisfaction (Alagarsamy & Mehrolia, 2023).

Privacy’s role in shaping trust in AI chatbots is supported by similar evidence from a study of South African banking customers which showed that digital privacy concerns made customers less willing to share personal information with chatbots, and that trust in the bank influenced engagement with its chatbot (Lappeman et al., 2023) emphasizing that chatbot trust is closely tied to the long-term reputational relationship between the customer and the bank.

Yatawara et al., (2025) systematic review on consumer adoption of AI-driven chatbots shows that trust in chatbots is highly influenced by the design, including its level of anthropomorphism.

Together, these studies show that trust in chatbot-mediated communication is not one-sided. It is shaped by brand perception, how privacy is handled, the design and the wider social context.

Closely related to trust, but conceptually different, is perceived authenticity. This refers to the extent to which customers experience chatbot interactions as genuine and transparent rather than scripted.A study by Marjerison et al., (2025), grounded in the Technology Acceptance Model found that when users perceive an AI chatbot as genuine and trustworthy, they are more likely to engage with it and adopt it, which reduces perceived risk. This suggests authenticity is just not a desirable feature but a requirement for positive engagement.

Chatbot identity framing is fundamental to this construct. It influences trust and emotional connection. Moderate human-likeness produced the best outcomes in terms of trust and perceived service quality, while making a chatbot too human-like brings discomfort and transparency concerns reducing brand attachment (Umair et al., 2026). If users realise they had been interacting with a machine they thought was human, they may feel deceived, which damages both their experience of the service and their relationship with the brand.

In a study on the value of chatbots in public relations and how businesses can use them to develop long lasting and more personalized relationships with customers that eventually strengthen their trust toward the company, Men (2022), stated that when organizations are open and honest about use of new technology, and present it in a modern way, more capable and friendly, this can improve stakeholders relationships and brand perception.

Researchers are not only looking at how useful chatbots are, but also at how they make customers feel during interactions.Research on emotional AI found that chatbots displaying empathic response styles were perceived as warm, a quality normally associated with humans, and influenced satisfaction and reuse intentions. The users are also more likely to recommend the service and share their positive experience.This suggests that human-centered AI can cultivate relational outcomes (Rohden & Espartel, 2026).

Nguyen et al.,(2023) found that human-like features in chatbots, such as natural conversation style and using emojis, influences perceived chatbot competence and authenticity, improving customer engagement. This indicates that chatbot persona design requires deliberate alignment, and for banks seeking to position chatbots as credible communication channels, this means chatbot design should be treated as an important strategic communication decision, not just a technical task.

Alshibly et al.,(2024) research on bank customers in Jordan revealed reliability and personalization greatly influence customer satisfaction directly and indirectly.

A substantial amount of research has examined the conditions under which chatbot interactions create negative perceptions and cause communication failures, a dimension with direct implications for corporate reputation management. Ranieri et al., (2024), analysed 7,167 conversations between customers and a chatbot over a period of 2 years and observed that unsatisfactory responses by the chatbot can affect customer perceptions of the company.

(Følstad et al., 2024) discovered that conversation breakdown or failures, affects user trust and emotions. Findings from a study on misunderstanding and user dissatisfaction in

AI-Driven Chatbot interactions with consumers further shows the main reasons customers are dissatisfied are; chatbots inability to understand questions, wrong or incomplete answers, lack of personalization and emotional intelligence, and data privacy concerns.While chatbots work well for simple routine questions, people perceive them incompetent for complex or sensitive conversations (Alhajri et al., 2026).

Research by Ahmad Bhatti (2019) showed that the majority of customers of Kenyan financial institutions that interacted with chatbots generally reported positive experiences. He also noted a slow adoption rate which he argued may be due to preferred interaction with human agents over chatbots. This indicates that chatbot performance may not be enough for sustained adoption when customers associate quality financial communication with the interpersonal warmth human agents provide.

2.7 Research Gap and Study Positioning

The literature review reveals two linked research gaps: limited geographic focus and narrow disciplinary perspectives, gaps that together make this study necessary.

The most important gap is geographic coverage. Most studies on customer perceptions of AI chatbots in banking have been conducted in high-income, Western, or East Asian contexts, with little attention on African settings. Yatawara et al., (2025) systematic review of publications on Consumer adoption of AI driven Chatbots from 2017 to 2024 demonstrates dominance of studies from Asia, America, Europe and other regions with no African country represented among the leading research sites.

This geographic imbalance is not only about underrepresentation, it also raises important questions about applicability of findings from other social and geographical settings to the Kenyan context. Kenya is one of the most advanced digital financial markets in Africa with an increasing AI adoption which makes this geographic gap especially significant and makes Kenya significant for contextually grounded research.

The second gap is disciplinary framing. Most studies on customer perceptions of banking chatbots have been carried out in the information systems, marketing, consumer behavior, or human-computer interaction areas, leaving out the corporate communications angle, which focuses on how organizations strategically build stakeholder relationships, shape their public image, and protect brand reputation through intentional communication choices (van Riel & Fombrun, 2007).

From a corporate communications point of view, a chatbot represents the brand, helps build relationships, and a channel of institutional voice. How well it interacts with the customers can improve or weaken the organisation's overall image. As established by Men (2022), chatbots interactions can affect the public perception of a company's character and competence.

Yet literature has not yet clearly looked at how bank customers, not only in Kenya, perceive and evaluate chatbots in terms of relationships and reputation. This gap has practical as well as theoretical importance, as banks looking to know whether chatbots help their communication and brand image, not just whether they work technically, currently lack evidence.

Bhatti (2019) remains the only study to have explored chatbot perceptions in the Kenyan financial sector, and while his findings provide a valuable starting point, the study was carried out before the substantial expansion of chatbot deployment by major Kenyan banks between 2019 and 2025 and does not focus on the corporate communications dimensions of chatbot-mediated customer relationships.

Critical questions remain unanswered in the existing literature: How do customers perceive AI chatbots as channels of institutional communication? Does chatbot performance shape their perceptions of the bank as an organisation? These questions cannot be answered well using studies from other countries or settings. They need research that is based on the Kenyan context itself.

3.0 Research Methodology

3.1 Research Design

This study utilizes a quantitative, cross-sectional research design. As the research questions seek to measure the extent of customer trust in AI-generated interactions, examine how customers perceive the effectiveness of AI-driven communication channels compared with traditional human interaction for simple queries, identify the challenges encountered during engagement with AI-driven communication channels, and explore what improvements customers suggest for enhancing AI-based communication. Quantitative data is necessary to reveal meaningful patterns and relationships across a wide range of respondents.As Creswell, (2014) states, quantitative research is a way of testing ideas or theories by examining how variables relate to each other. The variables can be measured typically on instruments, and the numerical data can be analyzed using statistical procedures.

The research strategy applied is a quantitative survey. Compared to other strategies such as experiments, which require controlled conditions that are not suitable for studying real-world customer perceptions, or case studies, which focus on in-depth exploration of a single context, surveys provide the breadth and efficiency required to fulfill the study's goals and objectives across different banks and demographic groups.

Although a qualitative or mixed methods approach could have offered more detailed insights into individual customer perceptions and experiences, these approaches are more suitable for exploratory research where little is known about the topic being researched.

Since there is existing literature on AI chatbots adoption which provides sufficient theoretical foundation, a quantitative approach is more appropriate for measuring and comparing perceptions across a large sample.The primary data collection instrument will be a structured self-administered questionnaire, which will help to ensure consistency in responses among respondents and facilitate meaningful comparisons across demographic groups, customers from different banks, and levels of prior chatbot experience. A questionnaire is especially suitable for this study as it allows for the effective collection of data from a large number of banking customers (Pramod et al., 2016) in different locations in Kenya.

The cross-sectional design is particularly appropriate given the scope and timeframe of this study. Given that customer perceptions of AI chatbots in the Kenyan banking industry represent a relatively recent and evolving phenomenon, capturing a current overview is more meaningful than tracking longitudinal change at this stage of research.By collecting data from multiple respondents at a single point in time (Creswell, 2014), this design provides an efficient and representative summary of current customer perceptions and experiences within the Kenyan banking sector. The approach also aligns with the study's descriptive and comparative aims, without requiring the tracking of changes over time.

3.2 Target Population and Sampling Techniques

The target population for this research is customers of commercial banks in Kenya who have previously interacted with AI-driven chatbots as part of their banking experience. Focusing on customers with prior chatbot experience guarantees that respondents can provide informed and meaningful assessments of their perceptions, and challenges encountered during AI-driven interactions. A target sample of 100 respondents was set based on practical considerations, including time constraints and the accessibility of the target population.

This study applies convenience sampling, a non-probability sampling technique in which participants are selected based on their availability and accessibility (Creswell, 2014). Convenience sampling is widely used in studies where it is not practical to include every subject in the target population (Etikan, 2016). Given there is no publicly available all-inclusive list of Kenyan bank customers who have interacted with AI chatbots, a probability sampling technique would not be feasible within the scope and timeframe of this research.

WhatsApp is one of the most widely used communication platforms in Kenya (Wanyoike, 2026), making it a suitable channel for reaching a geographically dispersed population. To qualify for participation, respondents must confirm that they are customers of a Kenyan bank and have previous interaction with an AI chatbot as part of their banking experience. A screening question will be used at the beginning of the questionnaire to filter out respondents who do not meet this criterion, thereby maintaining the integrity of the target population.

A major disadvantage of convenience sampling is the risk of bias (Etikan, 2016), as the sample may not be fully representative of the broader population of Kenyan bank customers. Especially, recruiting participants primarily through online platforms may overrepresent younger, more digitally literate customers while underrepresenting older customers or those in rural areas with limited internet access. To moderate this, efforts will be made to encourage participation across different demographic groups, including varying age groups, genders, income levels, and geographic locations. Findings will also be interpreted with this limitation in mind.

3.3 Data Collection

Data for this study was collected using a structured self-administered questionnaire developed specifically for this research. It was designed to translate the main constructs of the study, which are : *trust, perceived usefulness, satisfaction and frustration, and brand perception* into measurable variables that could be easily analysed. The development of the questionnaire was informed by the study's research questions and existing literature on AI chatbot adoption, customer experience, and technology acceptance in banking contexts.

The questionnaire has six sections, A to F. It starts with a screening and termination question at the beginning where respondents are first asked whether they have previously interacted with an AI chatbot from a Kenyan bank. Those who have not are automatically directed to the end of the survey, ensuring only those with relevant chatbot experience proceed to the main questions therefore maintaining the relevance and integrity of the data collected.

Section A captures respondents' chatbot usage background, identifying the specific bank whose chatbot was used and the frequency of chatbot interactions. This contextual information provides a basis for understanding respondents' level of familiarity and experience with AI banking chatbots prior to their responses to the main sections of the questionnaire.

Sections B to F contain the main survey questions. The questionnaire closes with a standalone open-ended question inviting respondents to suggest improvements to banking chatbots. Although optional, this question provides additional qualitative insights that complement the quantitative data collected in the previous sections.

The key variables of the study were operationalised as follows. Chatbot experience (Section B, items 4–7) was measured through four items assessing response speed, ease of use, accuracy of information, and effectiveness in resolving customer issues. Trust and security (Section C, items 8–9) was operationalised through two items exploring respondents' trust in chatbot-provided information and their perception of data safety. Satisfaction and frustration (Section D, items 10–13) was measured through four items capturing overall satisfaction, perceived improvement to the banking experience, frustration when chatbots fail, and comparative satisfaction with chatbots versus human agents for simple queries. Brand and communication perception (Section E, items 14–16) was operationalised through three items measuring the impact of chatbot performance on the bank's image, perceived efficiency of chatbot communication, and the association of chatbots with banking innovation.

Items across Sections B to E were measured using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The Likert scale is widely used in attitude and perception research as it captures the degree to which respondents agree or disagree with a given statement (Sullivan & Artino, 2013).

Section F captures demographic information, including age, gender, and level of education, which will be used to facilitate comparisons across different respondent subgroups.

The questionnaire was administered digitally through Google Forms and the survey link was distributed to respondents via WhatsApp.

3.4 Validity and Reliability

Validity refers to the extent to which a research instrument measures what it is intended to measure (Field, 2018).

In survey-based research, a common threat to internal validity is response bias, where respondents give answers they think are socially desirable rather than their genuine opinions. To reduce this, the survey was designed to be fully anonymous, with no personal data collected, thereby encouraging honest and candid responses. A screening and termination question was also incorporated at the beginning of the questionnaire to ensure that only people with experience interacting with AI chatbots from Kenyan banks could continue to the main sections of the survey, reducing the risk of uninformed responses altering the findings. In addition, the use of a structured questionnaire with the same standardised items ensured that all respondents are answering the same questions under the same conditions, reducing differences in how the questions are interpreted and thereby strengthening the internal validity of the study.

Construct validity refers to the degree to which the items in a questionnaire accurately capture the hypothetical constructs they are intended to measure (Creswell, 2014).

To ensure construct validity, the questionnaire items were developed based on a detailed review of existing literature on AI chatbot adoption, customer experience, and technology acceptance in banking contexts. Each construct; trust, perceived usefulness, satisfaction and frustration, and brand perception was operationalised using multiple items designed to capture different dimensions of the construct, reducing the risk of any single item misrepresenting the broader concept.

Prior to the main data collection, the questionnaire was piloted with 5 participants to check the clarity, wording, and flow of the survey items. The pilot revealed two areas requiring correction. First, the estimated survey completion time stated on the introductory page was adjusted to reflect the actual time taken by pilot participants, which was shorter than initially indicated. Second, several questions that had been mistakenly included at the end of the survey were removed, among them items requesting respondents' names and email addresses. As the survey was designed to be anonymous, the inclusion of these items was inconsistent with the study's ethical approach and was corrected before the main data collection began. The Pilot responses were deleted from the final dataset to ensure that only data from the main data collection phase were analysed.

These changes strengthened the construct validity of the instrument by ensuring that the final questionnaire was clear, consistent, and aligned with the study's research objectives and its ethical standards.

Reliability refers to the consistency of a research instrument. That is, the extent to which it produces stable and consistent results across different respondents and situations (Field, 2018).

To assess the reliability of the questionnaire, Cronbach's alpha will be calculated for each construct following data collection. Cronbach's alpha is commonly used in Likert-scale surveys, with a commonly accepted score of 0.70 or above indicating acceptable reliability(Hair Jr et al., 2018). Constructs falling below this threshold will be reviewed and interpreted with caution.

Additionally, the use of standardised, closed-ended questions throughout the questionnaire reduces differences in interpretation across respondents, further supporting the reliability of the data collected.

3.5 Ethical Considerations

This study was conducted in line with established research ethics principles applicable to online survey research. The questionnaire was created with key ethical safeguards in mind, including voluntary participation, anonymity, confidentiality, and the right to withdraw at any point by closing the survey. These measures are consistent with the ethical standards recommended for research with human participants (Oates et al., 2021).

Informed consent was obtained prior to participation through a clear opt-in action on the introductory page of the survey. This page outlined the purpose of the study, the estimated time required to complete the survey, and the intended academic use of the data, ensuring that respondents could make an informed and voluntary decision before proceeding.

To protect respondents' privacy, the survey collected demographic data only necessary for analysis : age, gender, and education level. No names, account details, phone numbers, email addresses, bank account identifiers, or other direct personal data was requested or stored. This design reduces privacy risks and supports anonymization of responses.Only data necessary for answering the research questions will be analyzed. The dataset will be stored securely, with access restricted to the researcher and the academic supervisor.

Although the study was conducted in Kenya, General Data Protection Regulation (GDPR) principles were still relevant given the EU academic context within which the research was produced, and the possibility of EU-based supervision or data processing. Under GDPR, valid consent must be freely given, specific, informed, and unambiguous and may include electronic means such as ticking a box on a website or another statement that clearly shows the person agrees to how their data will be used (THE EUROPEAN PARLIAMENT AND THE COUNCIL OF THE EUROPEAN UNION, 2016). As the survey collects no personally identifiable information, the data falls outside the direct scope of GDPR, as principles of data protection and this regulation do not apply to personal data rendered anonymous.

3.6 Data Analysis Strategy

Data analysis will be conducted using IBM SPSS Statistics. The analysis will be organised into two successive stages, preliminary analysis and main analysis.

Prior to hypothesis testing, preliminary analysis will be conducted to clean and prepare the data. Descriptive statistics including frequencies and percentages, will be computed to summarise the demographic characteristics of respondents in terms of age, gender, education level, bank name, and frequency of chatbot use. Construct-level descriptive statistics will also be computed to provide an overview of customer perceptions across the four main constructs, Perceived Usefulness, Trust, Satisfaction and Frustration, and Brand Perception thereby addressing the main research question.

Likert scale responses will be treated as ordinal data at the individual item level and as approximately continuous data at the construct level, where composite scores will be computed by averaging the relevant items for each construct. Mean scores will be interpreted using an interval scale derived by dividing the total scale range by the number of response options [(5-1)/5 = 0.80], producing interpretation ranges from Strongly Disagree (1.00–1.80) to Strongly Agree (4.21–5.00).

Internal consistency reliability will be assessed for each construct using Cronbach's alpha prior to the main analysis. A threshold of 0.70 will be adopted as the minimum acceptable level of reliability, consistent with widely accepted conventions in quantitative social science research (Hair Jr et al., 2018).

The main analysis will involve hypothesis testing using three statistical techniques, selected on the basis of the nature of each hypothesis and the level of measurement of the variables involved.

Spearman's rho correlation will be used to test H1 through H4, which examine relationships between pairs of ordinal variables at the individual item level. Spearman's rho was selected as the appropriate test given the ordinal nature of the individual variables to be analysed (Field, 2018). This test will be used to assess the strength and direction of relationships between trust and satisfaction (H1), satisfaction and perceived communication efficiency (H2), frustration and negative brand impression (H3), and perceived chatbot effectiveness compared to human agents and communication efficiency (H4).

Simple linear regression will be used to test H5 and H6, which examine whether Perceived Usefulness significantly predicts Satisfaction and Trust respectively. Regression was selected over correlation for these hypotheses as it tests the predictive relationship between an independent and a dependent variable, rather than mere association (Creswell, 2014). Composite scores will be used as variables for regression analysis as they approximate continuous data, satisfying the assumptions of linear regression.

One-Way ANOVA will be used to test H7 and H8, which examine whether perceived usefulness and satisfaction and frustration differ significantly across age groups and education levels respectively. One-Way ANOVA was selected as it is the appropriate test for comparing means across three or more independent groups (Field, 2018). Prior to each ANOVA, Levene's test for homogeneity of variances will be conducted to verify that the assumption of equal variances across groups is met. Where group sizes are too small for reliable analysis, groups will be merged prior to testing. Post hoc Tukey HSD tests will be conducted following each ANOVA to identify which specific group pairs differ significantly from each other.

4.0 Data Analysis and Interpretation

4.1 Preliminary analysis

4.1.1 Data cleaning and Preparation

Prior to analysis, the raw dataset was carefully cleaned and prepared to ensure the accuracy, consistency, and integrity of the data. Below are the steps:

The survey collected a total of 193 responses. To facilitate efficient analysis, all variables were first renamed from their original long-form question text to short standardised names, Q1- Q20 within SPSS.

The first cleaning step was to remove respondents who answered "No" to the screening question, confirming they had not previously interacted with an AI chatbot from a Kenyan bank. Since the study was only targeting customers with direct chatbot experience, these respondents were ineligible and therefore deleted. Following this step, 119 respondents remained.

The second cleaning step was to remove respondents from banks other than the three main banks used in this study; Equity Bank, Absa Bank, and KCB Bank. The questionnaire listed nine bank options, however only these three banks were retained for analysis as they were the only ones that had deployed AI chatbots at the time of data collection. As a result, 77 respondents remained. However, upon reviewing the data, 19 respondents were found to have selected more than one of the usable banks. Since the questionnaire was designed to capture experience with only one bank's chatbot, these responses were recoded to keep only the first bank selected, assuming this represented the respondent's main chatbot experience. This recoding was done manually. Once this was completed, the final usable sample was 96 respondents.

Next, the timestamp column was removed from the dataset because it was not a research variable and was not required for analysis. All remaining variables were then coded numerically and assigned value labels, to facilitate statistical analysis.

This cleaned and prepared dataset of 96 respondents therefore formed the basis for all subsequent preliminary and main analyses presented in this chapter.

4.1.2 Demographic Profile of Respondents

Following the final usable sample of 96 respondents retained for analysis. The demographic profile of this sample is presented below in terms of bank name, frequency of chatbot use, age, gender, and education level.

Frequencies

Statistics

		Bank Name	Frequency	Age	Gender	Education Level
N	Valid	96	96	96	96	96
	Missing	0	0	0	0	0

Frequency Table

Bank Name

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Equity Bank	57	59.4	59.4	59.4
	Absa Bank	18	18.8	18.8	78.1
	KCB Bank	21	21.9	21.9	100.0
	Total	96	100.0	100.0	

Frequency

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1-2 times	36	37.5	37.5	37.5
	3-5 times	30	31.3	31.3	68.8
	6-10 times	11	11.5	11.5	80.2
	More than 10 times	19	19.8	19.8	100.0
	Total	96	100.0	100.0	

Age

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	18-24 years	24	25.0	25.0	25.0
	25-31 years	40	41.7	41.7	66.7
	32-39 years	23	24.0	24.0	90.6
	40+ years	9	9.4	9.4	100.0
	Total	96	100.0	100.0	

Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	46	47.9	47.9	47.9
	Female	50	52.1	52.1	100.0
	Total	96	100.0	100.0	

Education Level

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Secondary education	3	3.1	3.1	3.1
	Diploma	13	13.5	13.5	16.7
	Bachelor's degree	60	62.5	62.5	79.2
	Master's degree or higher	20	20.8	20.8	100.0
	Total	96	100.0	100.0	

The majority of respondents were customers of Equity Bank, accounting for 57 respondents (59.4%) of the total sample. KCB Bank customers comprised 21 respondents (21.9%), while Absa Bank customers accounted for 18 respondents (18.8%). The high representation of Equity Bank customers reflects the bank's large customer base in Kenya and its early and widespread deployment of AI chatbot services, through its EVA chatbot.

Most respondents reported relatively infrequent chatbot use. Over a third of the respondents (37.5%) had interacted with a banking chatbot only 1-2 times, while 30 respondents (31.3%) had done so 3-5 times. A smaller number reported more frequent use, with 11 respondents (11.5%) interacting with a chatbot 6-10 times and 19 respondents (19.8%) interacting with one more than 10 times. These results indicate that while AI chatbot services are available across the three banks, their use remains relatively low among Kenyan banking customers, with most respondents having only minimal experience with the technology.

The sample was predominantly young. The largest age group was 25-31 years, comprising 40 respondents (41.7%), followed by 18-24 years with 24 respondents (25.0%). Together these two groups made up 66.7% of the total sample, indicating that younger customers are more likely to engage with digital banking services. Respondents aged 32-39 years accounted for 23 respondents (24.0%), while those aged 40 years and above formed the smallest group, with only 9 respondents (9.4%). The underrepresentation of older customers aligns with existing evidence on digital technology adoption in Kenya, where younger users tend to engage more frequently with AI-powered interfaces and older customers may find them difficult to use (Ministry of Information, Communications and the Digital & Economy (MICDE), 2025).

The gender distribution of the sample was broadly balanced. Female respondents slightly outnumbered male respondents, with 50 females (52.1%) and 46 males (47.9%). This near-equal distribution improves the gender representativeness of the sample and reduces the risk of gender bias in the findings.

The sample was highly educated.Most respondents held a Bachelor's degree, accounting for 60 respondents (62.5%). A further 20 respondents (20.8%) reported a Master's degree or higher, while 13 respondents (13.5%) had a Diploma.Only 3 respondents (3.1%) had secondary education as their highest level of qualification. The high percentage of degree-level respondents reflects the tendency of more educated customers to engage with AI-driven communication channels. This pattern is consistent with observations by the Kenyan Ministry of Information, Communications and the Digital & Economy (2025), which notes that customers with less formal education may find AI-powered interfaces difficult to use.

4.1.3 Reliability Analysis

Before hypotheses testing, the internal consistency reliability of each construct was assessed using Cronbach's alpha. The results are summarised below.

Table 1: Internal consistency reliability of constructs

Construct	**Items**	**Cronbach's Alpha**
Perceived Usefulness	4	0.847
Trust	2	0.827
Satisfaction and Frustration	4	0.634
Brand Perception	3	0.653

Perceived Usefulness and Trust demonstrated good internal consistency, with Cronbach's alpha values of 0.847 and 0.827 respectively, both comfortably exceeding the accepted threshold of 0.70. This indicates that the items within these constructs consistently measure the same underlying variable.

In contrast, Satisfaction and Frustration and Brand Perception returned marginal alpha values of 0.634 and 0.653 respectively, falling slightly below the 0.70 threshold. The lower reliability of the Satisfaction and Frustration construct may be attributed to its multidimensional nature, as it combines positive items (satisfaction and perceived improvement to banking experience) and a negative item (frustration when chatbots fail) within the same construct, which naturally reduces internal consistency. Similarly, Brand Perception returned a marginal alpha value, which may be partly due to the small number of items in the scale (three items) as scales with fewer items tend to produce lower alpha values (Field, 2018)

Despite these marginal values, both constructs were retained for analysis as their alpha values fall within an acceptable range for exploratory research (Hair Jr et al., 2018). However, findings related to these two constructs will be interpreted with appropriate caution.

4.1.4 Descriptive Analysis of Constructs

To address the main research question, '*How do Kenyan customers perceive AI-driven communication channels, specifically chatbots, in banking services?'* , construct-level descriptive statistics were computed for each of the four main constructs. Composite scores were calculated by averaging the relevant Likert scale items for each construct, and the results are presented below.

PU = Perceived Usefulness, TR = Trust, SF = Satisfaction and Frustration, BP = Brand Perception

Descriptives

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
PU	96	1	5	3.83	1.011
TR	96	1	5	3.49	1.287
SF	96	1	5	3.69	.909
BP	96	1	5	3.95	.953
Valid N (listwise)	96				

Mean scores for each construct were interpreted using an interval scale approach.The total scale range was divided by the number of response options.

(5-1)/5 = 0.80, producing the following interpretation ranges:

Mean Score	Interpretation
1.00 - 1.80	Strongly Disagree
1.81 - 2.60	Disagree
2.61 - 3.40	Neutral
3.41 - 4.20	Agree

4.21 - 5.00	Strongly Agree

Overall, Kenyan bank customers hold generally positive perceptions of AI chatbots as corporate communication channels, with all four constructs returning mean scores in the ‘agree’ range (3.41 - 4.20) on a five-point Likert scale.

Brand Perception recorded the highest mean score (M = 3.95, SD = 0.953), indicating that customers agree that AI chatbots influence their perception of the bank as an organisation. This suggests that chatbot deployment is broadly associated with positive corporate image, particularly in terms of communication efficiency and perceived innovation.

Perceived Usefulness returned the second highest mean score (M = 3.83, SD = 1.011), indicating that customers generally regard banking chatbots as useful communication channels. Respondents largely agreed that chatbots respond quickly, are easy to use, provide clear and accurate information, and resolve issues effectively. This aligns with the Technology Acceptance Model, which highlights perceived usefulness as a key driver of technology acceptance and adoption (Davis, 1989)

Satisfaction and Frustration recorded a mean score of (M = 3.69, SD = 0.909), suggesting that customers are generally satisfied with chatbot service. However, the relatively moderate mean compared to other constructs indicates that satisfaction is tempered by experiences of frustration when chatbots fail to perform as expected.

Trust recorded the lowest mean score among the four constructs (M = 3.49, SD = 1.287), though it still falls within the ‘agree’ range. The relatively high standard deviation of 1.287 indicates substantial variation in respondents' trust levels, suggesting that while customers generally trust chatbot communication, a notable percentage remain skeptical about the reliability of chatbot-provided information and the safety of their data.

4.2 Main Analysis

4.2.1 Hypotheses Testing

To test H1 through H4, Spearman's rho correlation was conducted for each hypothesis. Spearman's Rho was selected as the appropriate test given the ordinal nature of the individual variables analysed (Field, 2018). The results are presented below.

Table 2: Summary of H1-H4 results

Hypothesis	**Variables**	**r value**	**p value**
H1 - Trust = Satisfaction	**Q8 & Q10**	**0.503**	**<0.001**
H2 - Satisfaction = Bank's Communication Efficiency	**Q10 & Q15**	**0.672**	**<0.001**
H3 - Frustration = Negative Brand Perception	**Q12 & Q14**	**0.379**	**<0.001**
H4 - Chatbot effectiveness → Bank Communication Efficiency	**Q13 & Q15**	**0.337**	**<0.001**

H1: Trust in chatbot communication positively influences customer satisfaction.

This hypothesis examined the relationship between trust in chatbot communication (Q8) and customer satisfaction (Q10). The results showed a moderate, positive, and statistically significant correlation between the two variables ($r = 0.503$, $p < .001$).

These findings indicate that when customers trust the information from chatbots more, their overall satisfaction with chatbots as a communication channel also tends to increase.

H1 was therefore confirmed and the null hypothesis rejected.This finding is consistent with previous research which indicates that trust is a key determinant in chatbot interactions, as it influences technology acceptance, willingness to disclose personal information, customer engagement, and user satisfaction (Al-Oraini, 2025).

The moderate strength of the correlation further suggests that while trust is an important factor in driving satisfaction, other factors may also influence overall customer satisfaction with banking chatbots.

H2: Higher customer satisfaction with chatbot services enhances perception of the bank's communication efficiency.

The hypothesis explored the association between customer satisfaction (Q10) and perception of bank communication efficiency (Q15). A strong, positive, and statistically significant correlation was found between the two variables ($r = 0.672$, $p < .001$).

These findings suggest that as customer satisfaction with chatbot services increases, customers are more likely to perceive chatbots as making bank communication efficient.

It is important to note that while the correlation coefficient indicates a strong association between the two variables, correlation does not necessarily imply that one variable causes the other. The finding therefore indicates that satisfaction and perception of communication efficiency are strongly related, rather than saying that one clearly causes the other.

Hypothesis was therefore confirmed and the null hypothesis rejected.

H3: Higher customer frustration with chatbots negatively affects brand perception of the bank.

H3 investigated the relationship between customer frustration when chatbots fail (Q12) and negative brand impression of the bank (Q14). The analysis returned a weak, positive, and statistically significant correlation ($r = 0.379$, $p < .001$). These findings suggest that as customer frustration with chatbot failures increases, customers are more likely to form a negative impression of the bank.

Although the correlation coefficient is positive, this is expected since both variables measure negative experiences, frustration and negative brand impression, and therefore naturally move in the same positive direction. As frustration increases, negative brand impression also increases, which is consistent with the hypothesis that frustration negatively affects brand perception.

H3 was therefore confirmed and the null hypothesis was rejected. However the weak strength of the correlation, ($r = 0.379$) suggests that customer frustration is only one of several factors that may influence brand perception. Other variables such as overall service quality, trust, and satisfaction may also play a significant role in shaping customers' impression of the bank.

H4: Customers who perceive chatbots as more effective for simple queries compared to humans are more likely to perceive bank communication as efficient.

H4 examined the relationship between perceived chatbot effectiveness for simple queries compared to humans (Q13) and perceived bank communication efficiency (Q15).

The results revealed a weak, positive, and statistically significant correlation between perceived chatbot effectiveness for simple queries compared to humans and perception of bank communication efficiency ($r = 0.337$, $p < 0.001$).

It is important to note that while the correlation is statistically significant, the weak strength of the relationship, ($r = 0.337$), suggests that perceived effectiveness of chatbots for simple queries compared to humans is a limited predictor of perceived bank communication efficiency. This may indicate that customers evaluate communication efficiency based on a wider range of factors beyond simple comparative performance with humans.

H4 was therefore confirmed and the null hypothesis rejected.These findings suggest that customers who perceive chatbots as more effective than humans for simple queries are more likely to agree that chatbots make bank communication efficient, thereby contributing to the ongoing debate in the literature on whether customers prefer chatbots or humans.

H5: Perceived usefulness of chatbots is a significant predictor of customer satisfaction.

A simple linear regression was conducted to examine whether perceived usefulness predicts customer satisfaction with chatbot services.

Regression

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	PU_New[b]	.	Enter

a. Dependent Variable: S
b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.829[a]	.687	.684	.711

a. Predictors: (Constant), PU_New

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	104.147	1	104.147	206.211	<.001[b]
	Residual	47.475	94	.505		
	Total	151.622	95			

a. Dependent Variable: S
b. Predictors: (Constant), PU_New

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	-.251	.269		-.935	.352	-.785	.282
	PU_New	.996	.069	.829	14.360	<.001	.858	1.134

a. Dependent Variable: S

The regression model was statistically significant, $F(1,94) = 206.211$, $p < .001$, with perceived usefulness explaining 68.7% of the variance in customer satisfaction ($R^2 = .687$). Perceived usefulness was found to be a strong positive predictor of customer satisfaction ($\beta = .829$, $p < .001$). This indicates that customers who perceive chatbots as useful are significantly more likely to report higher satisfaction with chatbot services.Therefore, H5 was confirmed and the null hypothesis rejected.

H6: Perceived usefulness of chatbots positively predicts customer trust in chatbot communication.

A simple linear regression was carried out to test whether perceived usefulness of chatbots predicts customer trust in chatbot communication.

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	PU_New[b]	.	Enter

a. Dependent Variable: TR

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.620[a]	.385	.378	1.014

a. Predictors: (Constant), PU_New

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	60.517	1	60.517	58.809	<.001[b]
	Residual	96.730	94	1.029		
	Total	157.247	95			

a. Dependent Variable: TR

b. Predictors: (Constant), PU_New

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	.663	.383		1.729	.087	-.098	1.425
	PU_New	.759	.099	.620	7.669	<.001	.563	.956

a. Dependent Variable: TR

The results show that the model was statistically significant, $F(1,94) = 58.809$, $p < .001$, and perceived usefulness explained 38.5% of the variance in customer trust ($R^2 = 0.385$) Perceived usefulness was positive and significant ($\beta=0.620, p<.001$), indicating that higher perceived usefulness is associated with higher trust in chatbot communication. Therefore, H6 was confirmed and the null hypothesis rejected.

H7: Perceived usefulness of chatbots differs significantly by age group, with older customers rating chatbots as less useful than younger customers.

Oneway

Descriptives

PU_New

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Minimum	Maximum
18-24 years	24	3.93	1.040	.212	3.49	4.37	2	5
25-31 years	40	3.61	1.032	.163	3.28	3.94	1	5
32 years and above	32	3.73	1.092	.193	3.34	4.12	1	5
Total	96	3.73	1.051	.107	3.52	3.94	1	5

Tests of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
PU_New	Based on Mean	.075	2	93	.928
	Based on Median	.126	2	93	.882
	Based on Median and with adjusted df	.126	2	92.620	.882
	Based on trimmed mean	.152	2	93	.859

ANOVA

PU_New

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1.557	2	.779	.700	.499
Within Groups	103.401	93	1.112		
Total	104.958	95			

ANOVA Effect Sizes[a,b]

		Point Estimate	95% Confidence Interval Lower	95% Confidence Interval Upper
PU_New	Eta-squared	.015	.000	.079
	Epsilon-squared	-.006	-.022	.059
	Omega-squared Fixed-effect	-.006	-.021	.059
	Omega-squared Random-effect	-.003	-.011	.030

a. Eta-squared and Epsilon-squared are estimated based on the fixed-effect model.

b. Negative but less biased estimates are retained, not rounded to zero.

Post Hoc Tests

Multiple Comparisons

Dependent Variable: PU_New
Tukey HSD

(I) Age Groups ANOVA	(J) Age Groups ANOVA	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
18-24 years	25-31 years	.322	.272	.466	-.33	.97
	32 years and above	.201	.285	.760	-.48	.88
25-31 years	18-24 years	-.322	.272	.466	-.97	.33
	32 years and above	-.121	.250	.879	-.72	.47
32 years and above	18-24 years	-.201	.285	.760	-.88	.48
	25-31 years	.121	.250	.879	-.47	.72

Homogeneous Subsets

PU_New

Tukey HSD[a,b]

Age Groups ANOVA	N	Subset for alpha = 0.05 1
25-31 years	40	3.61
32 years and above	32	3.73
18-24 years	24	3.93
Sig.		.459

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 30.638.

b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

To test this hypothesis, a One-Way ANOVA was conducted with perceived usefulness as the dependent variable and age group as the independent variable. Prior to analysis, the original four age groups were recoded into three groups to address the small sample size in the 40+ years category (n = 9). Respondents aged 32-39 years and 40+ years were merged into a single group (32 years and above) resulting in three age groups for analysis: 18-24 years (n = 24), 25-31 years (n = 40), and 32 years and above (n = 32). Levene's test for homogeneity of variances was then conducted to verify that the assumption of equal variances across groups was met. The result was non-significant (F = 0.075, p = 0.928), confirming that the assumption of homogeneity of variances was satisfied and that the One-Way ANOVA was appropriate for this data.

The descriptive statistics revealed slight differences in mean perceived usefulness scores across the three age groups. Customers aged 18-24 years recorded the highest mean score (M = 3.93, SD = 1.040), followed by customers aged 32 years and above (M = 3.73, SD = 1.092), and customers aged 25-31 years recorded the lowest mean score (M = 3.61, SD = 1.032). Notably, the pattern did not follow a straightforward age gradient as predicted by the hypothesis. The oldest group scored higher than the middle age group, suggesting that the relationship between age and perceived usefulness is not linear in this sample. All three groups nonetheless fell within the ‘agree’ range on the five-point Likert scale, suggesting that customers across all age groups generally perceive chatbots as useful.

However the One-Way ANOVA revealed no statistically significant difference in perceived usefulness across the three age groups ($F = 0.700$, $p = 0.499$). The post hoc Tukey HSD test confirmed that no significant differences existed between any pair of age groups, 18-24 vs 25-31 ($p = 0.466$), 18-24 vs 32 and above ($p = 0.760$), and 25-31 vs 32 and above ($p = 0.879$).

H7 was therefore not confirmed and the null hypothesis not rejected. The results do not confirm that older customers rate chatbots as significantly less useful than younger customers. Furthermore the non-linear pattern observed in the descriptive statistics suggests that age alone may not be a reliable predictor of perceived chatbot usefulness among Kenyan bank customers, contrary to what existing literature on digital technology adoption suggests about older customers finding AI-powered interfaces more difficult to use.

H8: Customer satisfaction and frustration with chatbots differs significantly by level of education, with less educated customers reporting higher frustration than more educated customers.

Oneway

Descriptives

SF

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
Secondary/Diploma	16	3.44	1.195	.299	2.80	4.07	1	5
Bachelor's degree	60	3.68	.879	.114	3.46	3.91	1	5
Master's degree or higher	20	3.93	.703	.157	3.60	4.25	3	5
Total	96	3.69	.909	.093	3.51	3.88	1	5

Tests of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
SF	Based on Mean	2.561	2	93	.083
	Based on Median	1.907	2	93	.154
	Based on Median and with adjusted df	1.907	2	72.034	.156
	Based on trimmed mean	2.331	2	93	.103

ANOVA

SF

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2.127	2	1.063	1.294	.279
Within Groups	76.433	93	.822		
Total	78.560	95			

ANOVA Effect Sizes[a,b]

		Point Estimate	95% Confidence Interval	
			Lower	Upper
SF	Eta-squared	.027	.000	.105
	Epsilon-squared	.006	-.022	.086
	Omega-squared Fixed-effect	.006	-.021	.085
	Omega-squared Random-effect	.003	-.011	.045

a. Eta-squared and Epsilon-squared are estimated based on the fixed-effect model.

b. Negative but less biased estimates are retained, not rounded to zero.

Post Hoc Tests

Multiple Comparisons

Dependent Variable: SF
Tukey HSD

(I) Education Groups ANOVA	(J) Education Groups ANOVA	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Secondary/Diploma	Bachelor's degree	-.246	.255	.602	-.85	.36
	Master's degree or higher	-.487	.304	.249	-1.21	.24
Bachelor's degree	Secondary/Diploma	.246	.255	.602	-.36	.85
	Master's degree or higher	-.242	.234	.558	-.80	.32
Master's degree or higher	Secondary/Diploma	.487	.304	.249	-.24	1.21
	Bachelor's degree	.242	.234	.558	-.32	.80

Homogeneous Subsets

SF

Tukey HSD[a,b]

Education Groups ANOVA	N	Subset for alpha = 0.05
		1
Secondary/Diploma	16	3.44
Bachelor's degree	60	3.68
Master's degree or higher	20	3.93
Sig.		.165

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 23.226.

b. The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

To test this hypothesis, a One-Way ANOVA was conducted with satisfaction and frustration as the dependent variable and education level as the independent variable. Prior to analysis, the original education categories were recoded into three groups: Secondary/Diploma, Bachelor's degree, and Master's degree or higher to address the small sample size in the Secondary education category ($n = 3$).Levene's test for homogeneity of variances was then conducted to verify whether the assumption of equal variances across groups was met. The result was non-significant ($F=2.561, p=.083$), confirming that the assumption of homogeneity of variances was satisfied and that the One-Way ANOVA was appropriate for this data.

The descriptive statistics revealed slight differences in mean satisfaction and frustration scores across the three education groups. Respondents with a Secondary/Diploma recorded the lowest mean score ($M=3.44, SD=1.195$), followed by those with a Bachelor's degree ($M=3.68, SD=0.879$), and respondents with a Master's degree or higher recorded the highest mean score ($M=3.93, SD=0.703$). However, the pattern did not show a strong or consistent difference across education levels. All three groups fell within a fairly similar range, suggesting that customers across education levels generally reported comparable levels of satisfaction and frustration with chatbots. However, the One-Way ANOVA revealed no statistically significant difference in satisfaction and frustration across the three education groups ($F=1.294, p=.279$). The post hoc Tukey HSD test confirmed that no significant differences existed between any pair of education groups: Secondary/Diploma vs Bachelor's degree ($p=.602$), Secondary/Diploma vs Master's degree or higher ($p=.249$), and Bachelor's degree vs Master's degree or higher($p=.558$).

H8 was therefore not confirmed and the null hypothesis not rejected. Furthermore, the very small effect size ($\eta 2=.027$) suggests that education level was not a meaningful predictor of customer satisfaction and frustration with chatbots in this sample.

5.0 Discussion

The findings of this study collectively portray a complex picture of how Kenyan bank customers experience AI chatbots as corporate communication channels. Overall, respondents evaluated chatbots as broadly useful and reasonably efficient for handling routine banking queries, but their perceptions were strongly conditioned by relational and experiential factors: trust in the information provided by the chatbots, quality and speed of responses, and the ease of moving from automated to human assistance when needed. Demographic variables such as age and education, by contrast, played a more limited role. The sample was predominantly young and highly educated customers and evaluations of chatbots seemed to depend less on who the customers were and more on what the chatbots actually did in practice, and how they did it.

One of the clearest patterns in the findings is the close interconnection between trust, perceived usefulness and satisfaction. Customers who felt they could trust chatbot responses tended to be substantially more satisfied with chatbot-mediated communication overall.This pattern resonates strongly with experts arguments, that trust is a critical precondition for positive evaluations and adoption of technology in high-risk domains such as financial services (Gefen et al., 2003) This study also extends the traditional TAM model to incorporate trust as an antecedent variable. It posits that customer trust in AI chatbots directly and positively shapes both Perceived Usefulness and Perceived Ease of Use, which in turn influences satisfaction Behavioural Intention to Use. The findings in this study supports this extension, indicating that trust underpins how customers interpret and evaluate their interactions with AI-mediated channels.

The open-ended question at the end of the survey, '*What do you think banks should improve in their chatbots*?' provided insight into what 'trust' means to customers. Two respondents, for example, highlighted that "customer data privacy should be maintained always" and urged banks to "invest more in sophisticated AI models" and "AI user data security." These concerns are consistent with broader debates around AI in finance, where the black-box nature of algorithms, data privacy risks, and exposure to cyber attacks have been identified as key challenges in AI-driven financial services (Aldasoro et al., 2024). For customers in this study, trust was not simply about whether the chatbot sounded polite or friendly, it was grounded in beliefs about the bank's technical competence, ethical standpoint and capacity to protect sensitive information.

Perceived usefulness emerged as an equally powerful driver of satisfaction and trust. TAM predicts that perceived usefulness is one of the primary cognitive attitudes that direct an individual's intention to use a new technology (Davis, 1989). Bhattacherjee, (2001) in the Information Systems (IS) Continuance Model, also mentions perceived usefulness experienced from continued use as one of the factors that influence the intention to continue using a system.

In the context of AI chatbots in Kenyan banking, findings show that customers who perceived chatbots as useful were not only more satisfied but also more trusting of chatbot communication.

Several responses on what the banks should improve add important texture to this discussion. One customer said that “most answers given by bots are general” or that “sometimes the answers provided are not accurate/helpful,” which they found “quite frustrating.” Another proposed that chatbots should “use contextual awareness,” such as noticing when “a customer just had a transaction declined” and proactively offering to investigate the reason rather than opening with a generic greeting. Further urging banks to abandon technical “bank‑speak” and instead provide “clear, empathetic explanations that an average person can actually understand.” Taken together, these comments demonstrate that for customers, usefulness is multi‑dimensional. It includes accuracy, contextual sensitivity and clarity. When expectations are met, perceived usefulness and trust rise; when they are violated, customers become frustrated and less satisfied.

The results also reveal a strong connection between satisfaction with chatbots and perceptions of bank’s communication efficiency.Respondents who experience higher satisfaction were much more likely to agree that chatbots make communication with their bank efficient. This relationship is consistent with Expectation‑Confirmation Theory (ECT), which posits that satisfaction arises when a customer’s experience matches or exceeds their expectations before exposure to the product and that satisfied users are more likely to continue using a service and evaluate it positively (Oliver, 1980) ; (Bhattacherjee, 2001). In this study, many customers appear to have approached chatbots with the expectation that they would provide quick, convenient access to information without the need to queue at branches or wait on call‑centre lines. When those expectations were met, for example, when chatbots quickly provided account balances or simple procedural information, customers concluded that AI chatbots made bank communication more efficient.

This interpretation aligns with wider industry narratives that position AI powered chatbots as tools for “24/7 availability” and “real‑time responses,” (Behzad, 2023) enabling banks to resolve high volumes of simple queries at low marginal cost. In the Kenyan context, where mobile banking is well established and customers are familiar with performing transactions via their phones, it is not surprising that an AI chatbot could be seen as an efficient way to obtain information or complete routine tasks.

However, the qualitative data revealed the limits of this efficiency narrative. One respondent complained that “the chat box should be faster in giving responses,” and another, “sometimes it takes too long to answer simple questions.” For such customers, the chatbot falls short of delivering the expected efficiency. Instead, the chatbot becomes a barrier to resolution, undermining satisfaction and brand perception of the bank.

The findings also suggest that chatbots marginally outperforming humans on simple queries is insufficient to guarantee strong perceptions of communication efficiency. Customers who perceived chatbots as more effective than humans for simple tasks were somewhat more likely to rate communication as efficient, but the relationship was relatively weak. Open-ended responses suggested that chatbots should “give an option to request it to direct queries to humans” and that banks should “have human back ups that are on standby.” The findings suggest that customers may respond more positively to banking chatbots when human support remains accessible, particularly for complex or sensitive queries. A chatbot that is fast but offers no clear route to a human agent may be experienced as efficient in narrow functional terms, but deficient in terms of communication. The findings from the Kenyan banking industry suggest that customers evaluate efficiency holistically, incorporating not only how quickly the chatbot responds, but also how easily they can escalate to human support and how “human-like” the interaction feels.

The study also found that higher frustration with chatbots tended to be associated with more negative perceptions of the bank’s brand, although this relationship was of moderate magnitude. Frustration typically arose when chatbots offered generic or irrelevant responses, inaccuracy, or took too long to respond. In such cases, respondents did not simply blame “the technology”; they questioned whether the bank cared about their time, understood their problems, or invested adequately in customer service. The wider literature on AI in banking reflects similar concerns. The (Consumer Financial Protection Bureau, 2023) states that when a chatbot interaction fails to provide accurate, personalised assistance, particularly if customers are unable to reach human agents, their confidence and trust in their financial institution will diminish. The findings that frustration is linked with more negative brand impressions supports these concerns, when chatbot communication is experienced as unhelpful or obstructive, it can erode broader perceptions of the bank’s competence, attentiveness and trustworthiness.

A notable finding is the limited role of age and education in shaping customers’ perceptions of AI chatbots as communication channels. Although small differences emerged in mean scores, age groups did not differ significantly in their ratings of perceived usefulness, and education levels did not significantly differentiate levels of satisfaction or frustration. This is somewhat inconsistent with traditional “digital divide” narratives, which often portray older or less educated users as less comfortable with new technologies and more likely to struggle with digital interfaces. However, it aligns with more recent evidence from emerging‑economy contexts showing that once customers adopt mobile and digital banking, attitudes are strongly shaped by perceived usefulness, trust and risk rather than demographics alone (Jamshaid et al., 2025).

In Kenya specifically, the rapid diffusion of mobile money and mobile banking over the last decade has normalised digital financial behaviour across broad segments of the population. Against this backdrop, it is reasonable that even older customers in this research, many of whom are still in early middle age and hold tertiary qualifications, are sufficiently digitally literate that they do not perceive chatbots as naturally unfamiliar or difficult to use. Instead, they evaluate chatbot communication using the same criteria as younger users: Does it work? Is it accurate? Is it fast? Does it feel like the bank cares? In this sense, the study suggests that experiential and service‑quality factors are now more noticeable than traditional demographic divides for understanding perceptions of AI chatbots among Kenyan bank customers.

These findings fit within, but also extend existing literature. In the Kenyan context, prior research on mobile banking and digital financial services has largely focused on adoption drivers. Internationally, a growing number of studies have started to examine customer perceptions of AI chatbots in banking and other financial services (Kaakandikar et al., 2025); (Consumer Financial Protection Bureau, 2023). Many of these studies highlight themes similar to those identified here: customers appreciate convenience and 24/7 availability, but worry about data privacy, accuracy and the loss of human interaction. The results suggest that Kenyan customers share many of the same expectations and anxieties as customers elsewhere, but interpret them through the lens of an already mature mobile‑money and digital‑banking ecosystem.

6.0 Implications for banks and communication practice

From a practical standpoint, the findings convey several implications for banks seeking to position AI chatbots as credible corporate communication channels. First, improvements in perceived usefulness, is likely to yield significant gains in perceptions of brand perception and satisfaction. This means investing not only in natural-language processing and back-end integration to improve accuracy and contextual awareness, but also in the “surface” design of conversations. Responses need to be fast, clear, concise and free of unnecessary jargon, where technical terms are unavoidable, they should be accompanied by simple explanations.

Banks should also view chatbots and human agents as complementary. Customers in this research clearly valued the idea of human “backups” who could take over when the chatbot reached its limits. Providing a prominently displayed “speak with a human” option within the chatbot interface, and ensuring that handovers are smooth and well-timed, can help preserve trust and prevent frustration. This approach is in line with recommendations from regulators and industry analysts, who caution that over-automation without accessible human support can erode service quality and trust (Consumer Financial Protection Bureau, 2023).

Communication about data privacy and security should be more explicit. Given that trust emerged as a key driver of satisfaction and that respondents spontaneously raised concerns about data security and privacy, banks should not assume that technical safeguards are understood. Chatbots can be used to explain, in simple language, how personal data is encrypted, how customer identity is protected, and what customers can do if they suspect fraud. Transparent communication in this area can reinforce the perception that the bank is both technologically competent and ethically responsible.

Finally, since age and education did not appear to play a major role in this research, banks should not presume that older or less educated customers are naturally less capable of using chatbots. Instead, they should focus on designing chatbot interactions that are clear, trustworthy and responsive for all users. In practice, this means testing chatbot algorithms with diverse groups, including customers with varying levels of digital experience and language proficiency, and iterating on the basis of their feedback.

7.0 Limitations and further research

Several limitations of this study must be acknowledged. Since this study employs convenience sampling, the findings may not be fully representative of all Kenyan bank customers who interact with AI chatbots. Respondents were recruited primarily through WhatsApp therefore skewed towards younger, more digitally literate customers. The sample size (n = 96), while adequate for the analyses conducted, was relatively modest and also skewed toward highly educated respondents.This limits the generalisability of the findings and may partly explain the absence of strong age and education effects. Future research should seek larger and more diverse samples, including rural customers, older age groups and those with lower formal education, to examine whether similar patterns hold across the broader Kenyan population.

The study also relied on self-reported perceptions collected at a single point in time.Longitudinal studies could track how trust, usefulness and satisfaction evolve as customers gain more experience with chatbots or as banks upgrade their systems. Qualitative follow-up studies, such as in-depth interviews or focus groups would also be valuable for exploring in more detail how customers interpret AI-mediated communication, how they negotiate boundaries between chatbot and human support, and how these experiences shape their overall relationship with the bank.

A further limitation is that the study treated “AI chatbots” as a relatively unified category. In practice, there is considerable variation in chatbot design and capability across Kenyan banks, ranging from simple systems to more advanced conversational agents. Future research could compare specific implementations, examining how particular design choices (e.g., conversational style, transparency about limitations, integration with human support) influence trust, satisfaction and brand perceptions.

Comparison between AI-driven and human communication was operationalised using a single survey item focused specifically on perceived effectiveness of chatbots for simple queries. As a result, the findings do not capture overall customer satisfaction or frustration across different types of service interactions, such as complex problem-solving, complaint handling, or emotionally sensitive communication. Instead, the results should be interpreted as reflecting respondents’ perceptions of chatbot suitability and effectiveness in routine, low-complexity interactions compared with human agents. This narrower measurement scope may limit the extent to which the findings can be generalised to broader service contexts or used to make conclusions about overall channel preference between AI and human communication.

Despite these limitations, this study provides robust evidence that in the Kenyan banking sector, the success of AI chatbots as corporate communication channels hinges less on customer demographics and more on whether chatbots deliver trustworthy, high-quality service.

8.0 Conclusion

This study set out to examine how Kenyan customers perceive AI-driven communication channels, specifically chatbots, in banking services. The findings reveal a nuanced answer: customers broadly acknowledge the convenience and accessibility that chatbots offer, yet remain cautious due to concerns around trust, data security, and the limited capacity of current chatbot systems to handle complex interactions. The appetite for AI-powered banking exists, but it is conditional.

Customer perceptions were shaped by a dual tension. On one hand, chatbots were valued for their 24/7 availability, on the other hand, respondents expressed reservations about the ability to trust the chatbots particularly in the handling of sensitive financial data. These findings underscore that perception of chatbots go beyond technical functionality, trust and interaction quality matter equally.

The implications of this study extend across multiple stakeholders. For banking practitioners, the findings offer a clear mandate: investment in chatbot technology must be accompanied by investment in transparent data governance frameworks. For policymakers, particularly regulators within the Central Bank of Kenya, the study highlights the need for consumer protection guidelines that keep pace with the rapid deployment of AI communication tools. For scholars, this research fills a meaningful gap in the literature by positioning customer perceptions of AI communication channels within an African financial services context, a perspective that has been largely underrepresented in African digital communication studies.

The overarching message of this research is one of readiness. Kenyan banking customers are not resistant to AI. The technology exists; what is now required is the institutional will to deploy it thoughtfully with the Kenyan customer firmly at the centre. Banks that rise to this challenge will not only improve service delivery, they will earn the trust that makes digital relationships endure.

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Appendices

Appendix A: Research Questionnaire

Customer Perceptions of AI Chatbots as Corporate Communication Channels in the Kenyan Banking Industry

Master's Thesis Survey - Neu-Ulm University of Applied Sciences

Dear Respondent,

Thank you for participating in this research study examining how **Kenyan bank customers perceive AI chatbots (automated messaging tools like Equity Bank's EVA or Absa Bank's Abby) as corporate communication channels.**

Your insights will help improve banking services and contribute to academic research. This survey takes 8-10 minutes. All responses are anonymous, confidential, and used only for academic purposes. No personal data will be stored. Participation is voluntary, you can withdraw anytime by closing the survey.

Screening: This study targets customers who have used AI chatbots in a Kenyan Bank. If you haven't, the survey will end after the first question.

By clicking "Next," you consent to participate.

Section A: Screening and usage

1. Have you ever used an AI chatbot (automated messaging) from a Kenyan bank on WhatsApp, Facebook Messenger, or Telegram? (E.g: Equity Bank's EVA, Absa Bank's Abby)?

- Yes
- No

2. From which bank was the chatbot?

- Equity Bank
- Absa Bank
- KCB Bank
- Co-operative Bank
- NCBA Bank
- Standard Chartered Bank
- I&M Bank
- Stanbic Bank
- Other

3. How often have you interacted with a banking chatbot?

- 1-2 times
- 3-5 times
- 6-10 times
- More than 10 times

Section B: Experience

For Questions 4-16, please indicate your level of agreement using the following scale:
1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree.

4. The chatbot responds quickly.

5. The chatbot is easy to use.

6. The chatbot provides clear, accurate information.

7. The chatbot resolves my issue effectively.

Section C: Trust and security

8. I trust the information from the chatbot.

9. My data feels safe with the chatbot.

Section D: Satisfaction and frustration

10. I am satisfied with the chatbot service.

11. The chatbot improves my banking experience.

12. I feel frustrated when the chatbot fails.

13. Chatbots work well for simple queries compared with humans.

Section E: Brand and communication perception

14. Poor chatbot performance leaves a negative impression of the bank.

15. Chatbots make bank communication efficient.

16. Chatbots make the bank seem innovative.

Section F: Demographics

17. What is your age?

- 18-24 years
- 25-31 years
- 32-39 years
- 40+ years

18. What is your gender?

- Male

- Female

19. What is your highest level of education?

- Primary education
- Secondary education
- Diploma
- Bachelor's degree
- Master's degree or higher

Section G: Open-ended question

20. What do you think banks should improve in their chatbots? (Optional)

Thank you for completing this survey. Your time and responses are greatly appreciated.