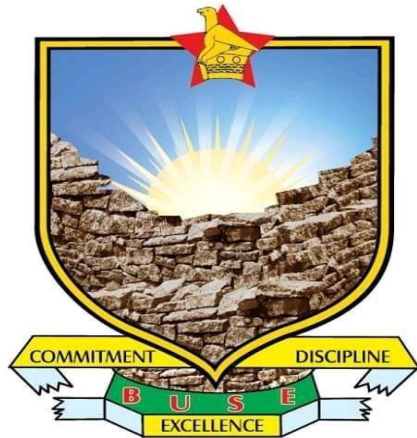


BINDURA UNIVERSITY OF SCIENCE EDUCATION



FACULTY OF COMMERCE

DEPARTMENT OF BANKING AND FINANCE

**THE EFFECTIVENESS OF NATURAL LANGUAGE PROCESSING (NLP) IN ENHANCING
CUSTOMER EXPERIENCE IN FINTECH: A CASE STUDY OF COMMERCIAL BANKS IN
HARARE CBD.**

BY

B224640B

**A DISSERTATION SUBMITTED IN PARTIAL FULFILMENT OF THE BARCHELOR OF
COMMERCE (HONOURS) DEGREE IN BANKING AND FINANCE AT BINDURA UNIVERSITY OF
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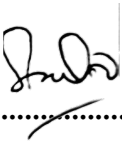
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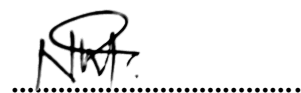
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DECLARATION

I declare that this dissertation is my original work. It is being submitted in partial fulfilment of the requirements of Banking and Finance degree in the Faculty of Commerce at Bindura University of Science Education.

A handwritten signature in black ink, appearing to be 'NM', is written above a horizontal dotted line.

SIGNATURE

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DEDICATION

This research is dedicated to my family who supported, encouraged and were very patient and had moral support during the study. They were always there to motivate me throughout the challenging part of reading, data collection, analysis and writing.

It is also dedicated to all the students and professionals, who are still working to acquire knowledge related to financial technology, artificial intelligence, and customer-centred service delivery, even amidst academic, professional and personal challenges. May this study help to a small extent in enhancing digital banking practices and customer service in Zimbabwe.

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I would like to thank those who have guided, assisted and given me feedback in the preparation of this research. The guidance that was given during the writing of the proposal, literature review, methodology and data analysis and final chapters reinforced the quality and focus of the study.

I wish to thank the bankers who were commercial bank customers, staff members, and focus group participants, whose opinions have been used in this research. They were ready to share their experience in digital banking, chatbots, virtual assistants and customer service technologies, allowing us to gain insight into the effectiveness of Natural Language Processing in the banking industry.

I would also like to thank other students, colleagues and friends who discussed, encouraged, and supported me throughout the research. They gave me some help to keep my mind on the project until it got done.

Lastly, I thank the authors, the researchers and scholars who have contributed to the conceptual, theoretical, methodological and empirical basis of this study. Their contributions to knowledge on FinTech, artificial intelligence, Natural Language Processing, customer experience and research methodology provided an important basis for this dissertation.

ABSTRACT

The aim of this study was to assess the impact of Natural Language Processing (NLP) on the Customer Experience (CX) in the FinTech industry in Harare CBD, with particular emphasis on commercial banks. The study aimed to explore the level of use of NLP technologies, analyze their effectiveness in improving customer experience, assess the impact of NLP based conversational systems on customer satisfaction, highlight the challenges in their implementation and suggest improvement strategies for financial institutions with the following objectives: to examine the level of utilization of NLP technologies, to evaluate their effectiveness in enhancing customer experience, to determine the influence of NLP based conversational systems on customer satisfaction, to highlight the challenges in their implementation, and to suggest improvement strategies for financial institutions. The mixed methods research was used. A total of 199 participants responded to the questionnaire out of the total target population of 218, representing 91.3% response rate. For qualitative data collection, a total of 13 out of 15 targeted subjects were interviewed and five out of five targeted subjects were held in focus group. Descriptive statistics, inferential analysis and thematic analysis were used to analyse the findings. The findings indicated that commercial banks are deploying NLP tools like chatbots, virtual assistants and automated response systems, with the extent of use varying by customer. The study also identified that NLP leads to better customer experience as it enables faster response times, convenience and availability, and reduces the need to rely on physical banking halls. However, responses are generic, support is limited in the local language, there is a concern regarding privacy, system downtime and poor customer education and poor escalation to human agents. The study found that the NLP can enhance the customer experience in banking as long as it is accurate, secure, inclusive, reliable, and with support from human assistance. The study suggested that commercial banks enhance the accuracy of the chatbots, integrate local languages, communicate privacy more effectively, educate customers, and establish feedback mechanisms for their NLP services.

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ACRONYMS

Acronym/Abbreviation	Meaning
AI	Artificial Intelligence
ATM	Automated Teller Machine
CBD	Central Business District
CRM	Customer Relationship Management
CX	Customer Experience
FinTech	Financial Technology
ICT	Information and Communication Technology
IVR	Interactive Voice Response
NLP	Natural Language Processing
RBZ	Reserve Bank of Zimbabwe
SERVQUAL	Service Quality Model
SMS	Short Message Service
SPSS	Statistical Package for the Social Sciences
TAM	Technology Acceptance Model
UTAUT	Unified Theory of Acceptance and Use of Technology
VIF	Variance Inflation Factor
POS	Point of Sale

CHAPTER I

INTRODUCTION

1.0 Introduction

The chapter introduces the study on the effectiveness of Natural Language Processing (NLP) in improving Customer Experience (CE) in FinTech-enabled Banking Services (FBS) of the commercial banks in Harare CBD. Banks are undergoing digital transformation to redesign, provide and measure their service delivery to customers, which increasingly relies on artificial intelligence (AI) to fuel automation, personalization and data-informed decision making (Huang and Rust, 2021). In this evolution, NLP plays a crucial role in enabling computer systems to understand, analyze, and produce the human language to power chatbots, virtual assistants, and automated customer support systems (Jurafsky and Martin, 2025). Banks in Zimbabwe have opened up digital service channels, but the ability to use AI advanced tools is still not even as a result of cost, skills, infrastructure and trust issues (Shambira, 2020). This chapter gives background information, problem statement, purpose, objectives, research questions, significance, assumptions, delimitations, limitations and key terms of the research and clarifies the scope of the research in relation to commercial banking services in the area.

1.1 Background of the Study

The financial services industry has shifted from branch-based delivery to digital platforms, integrating services such as payments, analytics, mobile and cloud-based platforms. Feyen et al. (2021) say that digital transformation is reshaping the way financial services are created, delivered and regulated in markets. Barroso and Laborda (2022) state that FinTech has been born of the use of new technologies in financial and investment services, leading to the creation of new business models and services. This is a worldwide change and in banking has given rise to the importance of speed, convenience, security and responsiveness as dimensions of customer experience. On the service-interface level, AI is a significant force for automating customer support

and analyzing vast amounts of customer data at the global level. Huang and Rust (2021) demonstrate the role of AI in service decision making in four ways: automation, predicting, personalization and understanding customers. Jurafsky and Martin (2025) present NLP as a language-processing field that enables systems to analyze, interpret and generate human language for computational tasks. Adamopoulou and Moussiades (2020) describe chatbots as dialogue systems designed to work with human-computer interactions through technologies like pattern matching, machine learning and natural language processing.

The digital finance and service model using artificial intelligence is emerging at varying speeds in African banking markets, due to different infrastructures, regulations, digital skill and customer trust levels between countries. According to Cheteni, Matsongoni and Umejese (2024), AI is transforming the South African fintech sector by providing opportunities for automation, operational efficiency and service innovation—all of which bring new challenges to the table regarding operational and governance concerns. In Kenya, Kuja (2024) discovered that customer experience has a significant positive relationship with the fintech product features and the cost of services, in Equity Bank's fintech products. According to Makore (2024), AI can be useful to financial inclusion in South Africa but good governance is essential to address cyber-security, liability and ethical challenges in financial services.

Digital banking has grown in Zimbabwe as commercial banks have adopted electronic channels to boost their customer coverage and convenience, coupled with transaction efficiency. According to Shambira (2020), customer satisfaction, cost reduction and risk management were cited as the reasons driving the adoption of AI in banking in Zimbabwe, but these were stymied by limited knowledge of AI, lack of resources, talent shortage, privacy issues and governance challenges. Kaondera et al. (2023) found that digital transformation positively contributes to customer relationship management in Zimbabwe's commercial banks. According to Tshuma, Towo and Dube (2024), Zimbabwean customers appreciate digital banking because it is convenient and easily accessible, but there are still challenges to overcome such as low technical literacy,

data security and privacy concerns, and low internet connectivity and high transaction fees.

Thus, the Zimbabwean banking sector is a suitable context for the study of NLP, as banks are already leveraging on digital channels and at the same time are still grappling with customer-service challenges associated with digital readiness. Shambira (2020) noted that very few banks in Zimbabwe were using AI to improve customer relationship with a chatbot. According to Ncube, Chinakidzwa and Mushayavanhu (2025), the type of tasks performed by the chatbot, the characteristics of the technology used, and conversational intelligence affect the satisfaction of the customers with the banking sector's customer service encounters in Zimbabwe. The results imply that the use of NLP tools has limited ability to enhance customer experience if their function does not match the consumer needs, banking activities and the service capability of the commercial banks.

Harare CBD is a key research location as it brings together the commercial banking branches, corporate customers and individual account holders, digital service points and high volume customer enquiries in a single urban financial centre. Kaondera, et al., (2023) are calling on commercial banks in Zimbabwe to go through the digital transformation processes which will equip them with tools that will help enhance customer relationship management in the context of electronic banking. Although digital banking customers appreciate the convenience of digital channels, Tshuma, Towo and Dube (2024) indicate that Harare based banking customers still have digital banking challenges. The present study is motivated by the fact that there is limited empirical research that has been done to specifically evaluate the effect of NLP technologies on customer experience in commercial banks located in Harare CBD.

1.2 Problem Statement

A digital age is the new reality of the commercial banks in Harare CBD with customers increasingly demanding for fast, accurate, personalised and convenient digital service. The quality of interactions at each touchpoint in the service process, including digital channels that customers use prior to, during and after a transaction, influences the

customer experience. While they can minimize wait times and handle repetitive queries, NLP-driven chatbots and virtual assistants need to be accurate, understand context, be dependable, and escalate to human agents when necessary and earn customer confidence. AI adoption in banking is not uniform in Zimbabwe, earlier reported examples indicate that very few banks had used AI for customer interaction. Further, evidence from recent studies in Zimbabwe indicates that conversational intelligence and task-technology fit in the context of chatbots influences the satisfaction of the customer's encounter with customer service (Ncube, Chinakidzwa and Mushayavanhu, 2025). Digital skills, infrastructure, privacy issues, cost of digital solution implementation and customer awareness are, however, constraints that still limit commercial banks (Tshuma, Towo and Dube, 2024). Consequently, there is a lack of empirical evidence specific to Harare CBD commercial banks to suggest that NLP technologies are improving the level of customer experience. The study, therefore, fills the gap by focusing on NLP utilization, effectiveness, satisfaction outcomes, challenges to implementing NLP and recommendations for improvement for local commercial banks.

1.3 Purpose of the Study

The purpose of this study is to assess the effectiveness of Natural Language Processing technologies in enhancing customer experience in FinTech-enabled customer service among commercial banks operating in Harare CBD.

1.4 Research Objectives

The study is guided by the following objectives:

1. To examine the level of utilisation of NLP technologies among commercial banks in Harare CBD.
2. To evaluate the effectiveness of NLP technologies in enhancing customer experience in commercial banking services.
3. To determine the influence of NLP-based conversational systems on customer satisfaction.

4. To identify the challenges associated with implementing NLP technologies in commercial banking services.
5. To propose strategies that can improve the implementation of NLP technologies in commercial banks.

1.5 Research Questions

The study seeks to answer the following research questions:

1. To what extent are NLP technologies utilised by commercial banks in Harare CBD?
2. How effective are NLP technologies in improving customer experience in commercial banking services?
3. How do NLP-based conversational systems influence customer satisfaction?
4. What challenges do commercial banks encounter when implementing NLP technologies?
5. What strategies can be adopted to improve the use of NLP technologies in commercial banking services?

1.6 Significance of the Study

1.6.1 To the Body of Knowledge

The study adds to the existing body of knowledge in the fields of AI, FinTech, and customer experience, as it offers empirical evidence within the context of an emerging market banking environment. Significance of the study: This study is important because context-specific evidence on the impact of digital touchpoints on customer responses in service experience interactions is needed to support research on customer experience (Becker and Jaakkola, 2020).

1.6.2 To Commercial Banks

The results can help commercial banks to identify if NLP-based systems like chatbots and virtual assistants are beneficial to the speed, accuracy, availability, and satisfaction of their services. This is crucial as the effectiveness of chatbots will depend

on the fit of the conversational intelligence user tasks and the capability of the technology.

1.6.3 To Customers

The research could help customers by revealing areas of service gaps that banks should work on to offer more transparent, speedy and reliable digital services. Customer frustration due to automated systems that don't understand the customer's problem or escalate it to human support can be mitigated by improved NLP design.

1.6.4 To Policy Makers and Regulators

The findings of the study may be helpful for policy makers and regulators who are interested in responsible digital finance, customer protection, data privacy and innovation governance. This is important since governance, privacy and technical capacity constraints are barriers to the adoption of AI in Zimbabwean banking.

1.6.5 To the University

The study can be used for academic research in the field of finance, information systems, business management and digital innovation. It can also serve as a basis for further studies on NLP, AI service quality and customer experience in the financial services industry in Zimbabwe.

1.7 Assumptions of the Study

The study is based on the following assumptions:

- Harare CBD customers have adequate access to digital channels for commercial banks, and they gave informed answers.
- There are NLP technologies that are already implemented in commercial banks, which are meant to facilitate the service communication and customer assistance.
- The respondents will give their authentic experience with NLP banking services.
- The NLP technologies in banks can be measured using the customer experience measures like speed, accessibility, satisfaction, accuracy and trust etc.

1.8 Delimitations of the Study

The target population for the study is Commercial Banks that are operating in Harare CBD. The geographical focus is appropriate as Harare CBD is an important commercial banking hub and digital financial service utilization hub in Zimbabwe. The study is centered on the NLP applications for the end customers, such as the chatbots, virtual assistants, and automated response systems. To focus the study on customer experience rather than internal risk analytics, back-office AI applications like fraud detection, credit scoring and anti-money laundering systems are not included. The study also covers the timeframe of 2020-2025, as this indicates more recent trends in digital banking, AI and customer-service automation.

1.9 Limitations of the Study

The first constraint is that the study is geographically limited to Harare CBD only, and hence results may not necessarily reflect the customers' experience in rural and semi-urban banking markets. Second, it is possible that the customer response to the survey is influenced by recall bias and/or knowledge of the underlying technology and/or customer attitudes toward digital banking. The third constraint is technical detail about their NLP systems may not be made public due to confidentiality and cyber security concerns. The fourth restriction is the rapidly evolving nature of AI and NLP technology—new tools could be developed since data was collected and introduce new considerations for the long-term applicability of certain results. These constraints will be taken into account by applying well-defined research instruments and by analyzing the results in the context of the study.

1.10 Definition of Key Terms

Term	Definition
Financial Technology (FinTech)	FinTech refers to the application of digital technologies to financial activities, products, processes and business models in ways that transform

	financial service delivery. Barroso and Laborda (2022) explain that FinTech emerges from the use of new technologies in financial and investment activities.
Artificial Intelligence (AI)	AI refers to computational systems designed to perform tasks associated with human intelligence, including learning, reasoning, prediction and decision-making. Russell and Norvig (2021) describe AI as a broad field concerned with intelligent agents that perceive their environment and act to achieve objectives.
Natural Language Processing (NLP)	NLP is a branch of artificial intelligence concerned with computational methods for processing, analysing and generating human language. Jurafsky and Martin (2025) present NLP as a field connected to computational linguistics, speech recognition and language technologies.
Customer Experience	Customer experience refers to the customer's cognitive, emotional, behavioural and social responses that emerge across interactions with a firm. Becker and Jaakkola (2020) explain that customer experience is formed across touchpoints and cannot be reduced to one isolated transaction.

Chatbot	A chatbot is a conversational software agent that interacts with users through text or voice interfaces. Adamopoulou and Moussiades (2020) describe chatbots as natural dialogue systems that use technologies such as pattern matching, machine learning and natural language processing.
Virtual Assistant	A virtual assistant is an AI-enabled conversational system that provides user support through language-based interaction, task execution and personalised responses. Jurafsky and Martin (2025) show that advances in NLP and speech technologies support systems that interpret and respond to user requests.
Customer Satisfaction	Customer satisfaction refers to the customer's evaluation of whether a service experience meets or exceeds expectations. Ncube, Chinakidzwa and Mushayavanhu (2025) link satisfaction in chatbot service encounters to chatbot task-technology fit and conversational intelligence.

1.11 Chapter Summary

This chapter introduced a study on the effectiveness of Natural Language Processing in enhancing customer experience in FinTech-enabled banking services among commercial

banks in Harare CBD. The background followed a funnel approach by moving from the global setting to the regional African context, then to Zimbabwean banking experiences and the Harare CBD research gap. The chapter also presented the problem statement, purpose of the study, research objectives, research questions, significance, assumptions, delimitations, limitations and definitions of key terms. The next chapter reviews literature related to FinTech, artificial intelligence, NLP, customer experience and technology adoption in banking.

CHAPTER II

LITERATURE REVIEW

2.0 Introduction

This chapter reviews literature on the effectiveness of natural language processing in enhancing customer experience in fintech, with specific attention to commercial banks in Harare CBD. It covers conceptual review, conceptual framework, theoretical review, empirical review, research gap and chapter summary. The review is organized around the objectives utilization of NLP technologies, effectiveness of NLP in customer experience, influence of conversational systems on customer satisfaction, implementation challenges and improvement strategies. The discussion relies on recent fintech, digital banking, chatbot, customer experience and Zimbabwean banking studies to position the present research within current academic debate.

2.1 Conceptual Review

The conceptual review gives a description of the key factors that impact the Customer Experience (CX) relationship in commercial banking with NLP technologies. Conceptual clarification is relevant as customer experience in digital banking is multidimensional, including functional, emotional, relational and trust-based evaluations in the various service touchpoints (Becker and Jaakkola, 2020). In this study, the primary technology input is the utilization of the NLP, while service efficiency, personalization, conversational intelligence, satisfaction and trust related perceptions describe the way customers interact with a chatbot and/or a virtual-assistant (Ashfaq et al, 2020).

Figure 2.1: Conceptual framework for NLP-enabled customer experience in banking

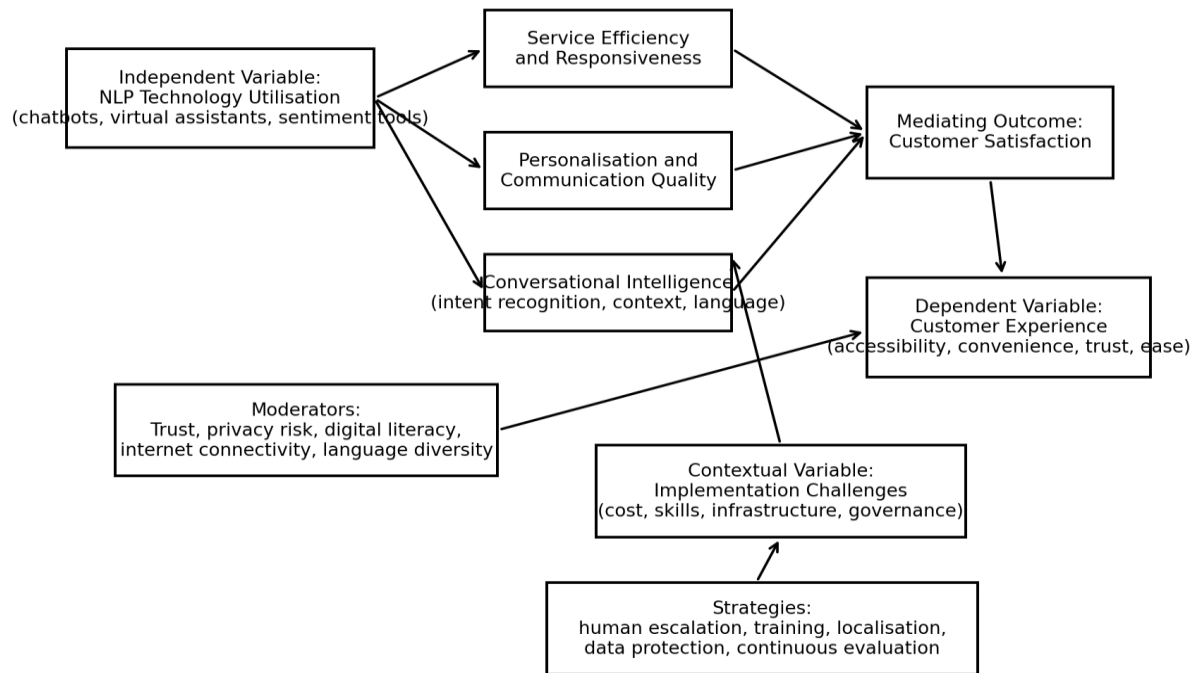


Figure 2. 1: Conceptual framework

Source: Adapted from Davis (1989),

Figure 2.2: Variable relationship map

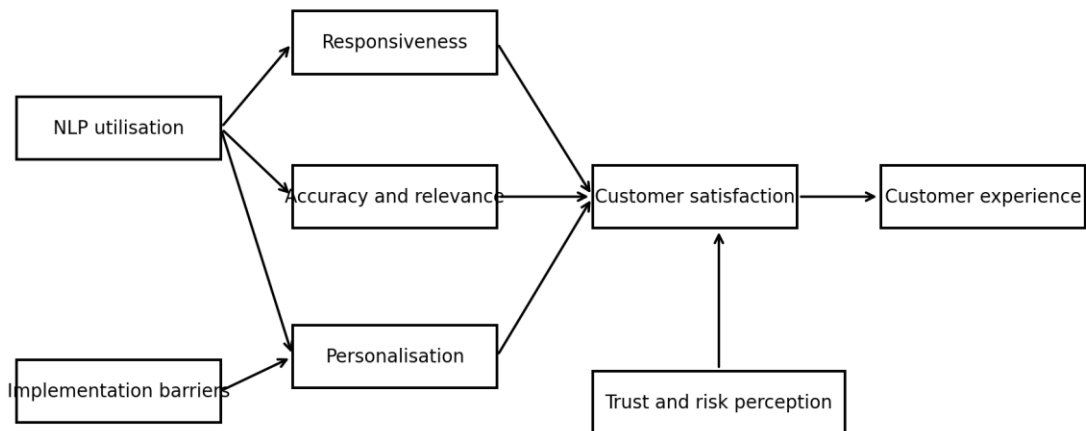


Figure 2. 2: Variable relationship map

Source: Adapted from Marak et al. (2025)

2.1.1 Natural Language Processing Technology Utilization

NLP technology utilization is defined as the degree to which banks are using language-based intelligent systems (e.g. chatbots, virtual assistants, automated response engines, sentiment analysis and text analytics) in customer-facing channels. NLP can be used to categorize customer intent, derive meaning from text and/or speech, and produce a response that's similar to human communication (Jurafsky and Martin, 2023). In commercial banking, utilization is important because customers increasingly expect instant information on balances, cards, payments, loans, complaints and branch services without waiting for call-center agents (Graham et al., 2025). For this study, NLP utilization is the independent variable because the presence, frequency and quality of NLP tools influence whether customers experience banking as accessible, responsive and convenient. In Harare CBD, utilization is also context-specific because banks serve high-volume customers who use mobile applications, websites and social-media channels for routine service encounters (Mtetwa, 2023).

2.1.2 Customer Experience

Customer experience is what customers think of the different direct and indirect engagements they have with a service provider throughout the customer journey. Customer experience is a multi-dimensional phenomenon that involves the cognitive, emotional, sensory, social and behavioural reactions to various service contact points (Gahler et al. 2023). Experience comes in many forms in digital banking: it is fast, convenient, correct, secure, empathetic, easy to use and allows the customer to solve problems without unnecessary hassle (Becker and Jaakkola, 2020). Since NLP technologies are expected to enhance the customer experience of digital banking interactions, this study views customer experience as the dependent variable. Customer experience relates more to commercial banks in Harare CBD since customers are likelier to compare the time spent on the chatbot to queues in a bank or delays at a call center and dealing with manual complaints (Makudza et al., 2024).

2.1.3 NLP-Based Conversational Systems

NLP based conversational systems are digital agents that communicate with humans by natural language, through text or voice. They consist of rule-based chatbots, artificial intelligence-enabled chatbots, virtual assistants, and hybrid service agents, which reference automated answers and then pass conversations to a human agent when needed (Adamopoulou and Moussiades, 2020). In the banking industry, conversation systems are employed for addressing commonly asked questions, assisting with transactions, delivering account details, and capturing complaints, among other functions, for digital onboarding (Graham et al., 2025). They play a key role in the present study as they are the most prominent of the customer touchpoints where NLP is being experienced in fintech banking. Their effectiveness relies on recognizing intent, relevance of the response, contextual memory, and handling errors and handling complex cases for human officers. In Zimbabwe, task-technology fit (TTF), conversational intelligence and customer service encounter satisfaction have been found to be directly relevant to customer experience (CE) when using chatbots (Ncube, Chinakidzwa and Mushayavanhu, 2025).

2.1.4 Service Efficiency and Responsiveness

Service efficiency indicates how speedily, accurately and with the least waste of resources, a bank provides its customers with service. The face of efficiency towards the customer is the responsiveness which is the degree to which the bank responds quickly and effectively to the needs of the customer (Parasuraman, Zeithaml and Berry 1988). NLP systems can enhance responsiveness by managing large volumes of routine enquiries that can operate outside of branch hours or the need for a physical queue or call center availability (Graham et al., 2025). Efficiency is a linking variable between NLP utilization and customer experience in this study as customers typically evaluate the performance of digital banking tools based on time savings and problem resolution. Digitalization in Zimbabwean banking has been correlated to improved performance but has caused concerns related to cyber risk, costs, and lack of specialist skill (Mtetwa, 2023).

2.1.5 Personalization and Communication Quality

Personalization is the provision of service responses that are responsive to customers' needs and history, their language, preferences and transaction context. Communication quality is defined as the clarity, relevance, completeness and tone of the service encounter communication (Huang and Rust, 2021). When NLP is used to analyze text from customer communications and to identify intent and offer contextually relevant guidance, not just canned answers, it adds to the personalization experience. (Jurafsky and Martin, 2023) This variable is connected to the study due to the fact that if a fintech customer feels understood by the NLP tools and not just processes it, they may value them. If a chatbot is not designed correctly, it might lead to frustration when it doesn't understand simple questions correctly, can't comprehend local expressions, or keeps giving irrelevant answers (Graham et al., 2025). Communication quality is critical in Harare CBD because the customers are using Shona, Ndebele or English with a Shona influence to seek assistance from digital banking (Ncube, Chinakidzwa and Mushayavanhu, 2025).

2.1.6 Customer Satisfaction

Customer satisfaction is the customer's evaluation of service after comparing what he/she expects to receive with what the service actually provides. In digital banking, system reliability, information accuracy, navigability of the banking system, swiftness of the system responses, and the individual's sense of security and successful solution of issues are the attributes that influence satisfaction (Ashfaq et al., 2020). In this study, customer satisfaction is considered as a mediating variable as positive interactions with the chatbot can lead to overall customer satisfaction, and consequently to the overall customer experience. When customers get timely and accurate answers, digital banking will be viewed as useful and repeated (Marak et al., 2025). But when automated systems deliver incorrect information, they can sometimes hinder a person's ability to access human support or even unable to resolve complex emotional complaints, this will reduce satisfaction. The empirical findings from Zimbabwe indicate that both the chatbot task-technology fit and conversational

intelligence have a significant impact on service encounter satisfaction in bank service delivery (Ncube, Chinakidzwa and Mushayavanhu, 2025).

2.1.7 Trust, Privacy and Perceived Risk

Trust indicates the customer's confidence that a bank and its digital systems are competent, honest and safe. Two key factors are privacy and perceived risk because banking chatbots deal with sensitive data such as card issues and complaints, transactions, and identification details (Huang and Rust, 2021). Perceived risk is a concept that negatively influences intention to use technology innovations when the data is feared to be misused, fraud, inaccurate advice, or loss of control (Marak et al., 2025). This variable is connected to the study, since if customers do not trust the automated service channels to be secure and reliable, then they will not be able to improve their experiences with NLP. Customer adoption of digital banking in Zimbabwe is more influenced by trust in the banking products, internet connectivity and cost of internet access, indicating that customer acceptance is influenced by factors beyond the availability of the technology (Mashizha, Gondongwe and Gumbo, 2025).

2.1.8 Implementation Challenges

Implementation challenges are the internal and external constraints that limit the effective deployment of NLP systems in banking. These constraints include high acquisition costs, weak data governance, limited technical expertise, cybersecurity threats, integration problems, unreliable connectivity and difficulty adapting systems to local language patterns (Mtetwa, 2023). Chatbot limitations also arise when systems cannot parse complex queries, detect emotion or distinguish between routine service requests and high-risk complaints (Graham et al., 2025). This variable is included because ineffective implementation can weaken the relationship between NLP utilization and customer experience. A bank may claim to use chatbots, but customers may still experience poor service if the chatbot is poorly trained, inaccurate or disconnected from back-office systems. In Zimbabwean banking, empirical evidence highlights the need to improve reliability, responsiveness and ease of use in chatbot banking (Makudza et al., 2024).

2.1.9 Strategic Implementation Capability

Strategic implementation capability refers to the bank's ability to convert NLP tools into reliable, secure and customer-centred service processes. This variable is included because a chatbot may exist technically but still fail to improve customer experience if it lacks governance, trained support staff, data protection, language localization and human escalation (Huang and Rust, 2021). In a banking environment, strategic capability also includes monitoring response accuracy, updating knowledge bases, auditing privacy risks and ensuring that automated answers remain consistent with bank policy (Cheng and Jiang, 2020). For commercial banks in Harare CBD, this variable links directly to the objective on improvement strategies because high transaction volumes and diverse customer needs require NLP systems that are managed as service infrastructure rather than as promotional digital features (Ncube, Chinakidzwa and Mushayavanhu, 2025).

2.2 Theoretical Review

The theoretical review anchors the study in established explanations of technology use and service quality. A theory is useful in this study because NLP-based banking tools do not affect customer experience automatically; customers must perceive them as useful, easy to use, reliable and capable of delivering quality service (Davis, 1989). The Technology Acceptance Model explains why customers may accept or reject chatbots and virtual assistants, while SERVQUAL explains how customers assess the service quality produced through those systems. Together, the theories support a balanced analysis of both adoption behaviour and service-performance outcomes (Parasuraman, Zeithaml and Berry, 1988; Marak et al., 2025).

2.2.1 Technology Acceptance Model

The Technology Acceptance Model was devised by Fred Davis in 1989 to explain why individuals accept or reject information systems. The theory assumes that perceived usefulness and perceived ease of use are the primary beliefs shaping users' attitudes and behavioural intention to adopt a technology (Davis, 1989). Perceived usefulness refers to the extent to which a customer believes that a system improves task

performance, while perceived ease of use refers to the degree to which the system is free from effort. In chatbot banking, these assumptions mean that customers are more likely to use NLP systems when they believe the tools save time, answer accurately and are easy to navigate (Hornuf et al., 2025).

The simplicity and its applicability to digital service adoption is a strength of the TAM. It can be used to measure technology acceptance with clear constructs that can be translated into questionnaire items, which is useful for quantitative analysis (Davis, 1989). A limitation is that it might not really capture the contextual factors that are crucial in emerging markets, for example, trust, culture, service risk, and internet access (Marak et al., 2025). This study is linked to the model due to the tools in the NLP being evaluated by commercial bank customers in Harare CBD based on their usefulness and ease of use. Customers will be more willing to accept chatbots when they provide timely, accurate, and secure support, leading to a positive customer experience (Ncube, Chinakidzwa and Mushayavanhu, 2025).

2.2.2 SERVQUAL Model

In 1988, Parasuraman, Zeithaml and Berry developed the SERVQUAL model which attempts to quantify the level of service quality by comparing the customer's expectations with the level of service provided. The model states that customers measure the quality of the service offered on five dimensions; reliability, responsiveness, assurance, empathy and tangibles (Parasuraman, Zeithaml and Berry, 1988). From a digital banking perspective, tangibles would refer to the digital face of banking, whereas reliability and responsiveness would refer to correct and timely automatic service responses. Empathy is demonstrated by the relevance and considers the customer in the chatbot interaction, whereas Assurance is demonstrated in the confidence of the customer in the bank to protect their data.

The appeal of SERVQUAL is its focus on technology availability versus customer's perceptions of service performance. This is because a bank with high-level NLP systems might be able to provide good NLP service but fail to provide positive experiences if the service feels unreliable, impersonal or unsafe (Becker and Jaakkola, 2020). One of

the disadvantages of SERVQUAL is that it was created before the presence of modern digital channels so it needs to be adapted to use on chatbots and virtual assistants. The model is therefore associated with this study because it helps to provide the dimensions of judgment on the effectiveness of the NLP in improving customer experience in Harare CBD commercial banks. Being responsive, reliable, and able to provide assurance and empathy is especially crucial when customers seek to resolve a pressing banking service problem via automated banking systems (Graham et al., 2025).

2.3 Empirical Review

The empirical review is a review of the previous studies and industry evidence related to the objectives of the study. It adopts a funnel structure, starting with global evidence, then regional African evidence, and finally the evidence in the context of Harare CBD in Zimbabwe. This structure seems appropriate as NLP in banking is influenced by the general fintech landscape, while the customer experience outcomes are influenced by the local infrastructure, customer literacy, language patterns and institutional readiness (Hornuf et al., 2025). Each subsection is related to the research objective in chapter one to ensure that the literature relates directly to the problem, methodology and discussion of the findings as per Ncube, Chinakidzwa and Mushayavanhu (2025).

2.3.1 Utilization of NLP Technologies among Commercial Banks

The experience of banks around the world indicates that AI and NLP are becoming a staple of their customer service operations, driving efficiency and innovation in digital engagement and aiding in decision-making. The number of people who own accounts increased to 76% in 2021, which broadened the customer base of digital financial channels, according to Demirgüç-Kunt et al. (2022). According to Chui et al. (2023), generative AI could generate \$200 billion to \$340 billion a year of value in banking, in part via customer-facing productivity gains and software-development enhancements.

Overall, fintech adoption in the region shows an increase in evidence across African markets; however, this process is not consistent across markets and services. If there is increased penetration, African fintech revenues are projected to grow from

approximately US\$10 billion in 2023 to as high as US\$47 billion by 2028, according to Kuyoro, Flötotto and Gathinji (2024). Hornuf et al. (2025) showed that customer-centered design, not just technology deployment, influences adoption of mobile fintech in Sub-Saharan Africa, with perceived usefulness and ease of use being the most important determinants of mobile fintech adoption.

In Zimbabwe, mobile apps, internet banking and platform-based service delivery has made digital banking easier to use and this has led to an increase in digital banking adoption. In Zimbabwe, Mtetwa (2023) discovered that most commercial banks had embraced digitalization to a higher degree, with innovation, fintech competition and globalization being the major drivers. Nonetheless, Mtetwa (2023) also identified barriers to NLP utilization, such as cybercrime risk, skill shortages and non-bank disruptors and technology cost as barriers, indicating that the use of NLP may be unevenly distributed in institutions.

In Harare CBD, use of NLP technologies needs to be viewed in the context of a high-density level commercial banking center where customers demand service delivery that is more expeditious than conventional branch service. Ncube et al., (2025) investigated Zimbabwean banking chatbots, highlighting that the fit between chatbots' tasks and their technology affects conversational intelligence and their satisfaction during a service encounter. This evidence equates to the need for analyzing the commercial banks in Harare CBD as it brings together high volumes of customers, digital banking enquiries and expectations of service quality, which can simultaneously highlight the commercial banks' strength and weakness when using NLP tools.

2.3.2 Effectiveness of NLP Technologies in Enhancing Customer Experience

Around the world, research shows that NLP helps to enhance customer experience by making banking more accessible, faster and more responsive. The study by Graham et al. (2025) revealed a positive attitude among banking and finance industry professionals towards chatbots for simple tasks due to convenience, availability and speed. Graham et al. (2025), however, pointed out that the accuracy and reliability issues diminish the

effectiveness when the customer query is complex, requiring an assessment of NLP performance based on task types and not simply as automation.

The impact of NLP in regional African markets is associated with the overall fintech maturity and digital access. In the study by Kamara and Yu (2024), the authors discovered a positive impact of FinTech adoption on the overall traditional financial inclusion index in the 22 Sub-Saharan African countries, but with varying results across the different dimensions. Kuyoro et al (2024) also observed that African fintech leaders predict that generative AI will enhance customer service by delivering highly customized products and services at a quick pace.

The research undertaken in Zimbabwe demonstrates that reliable and responsive chatbot banking has the potential to enhance customer experience, but only to a certain extent. Makudza et al. (2024) conducted a study that sampled 389 consumers in Zimbabwe who had interacted with chatbot banking and observed that there was a significant improvement in customer experience due to the use of chatbot banking. The same study revealed that the reliability, responsiveness, and ease of use need to be improved too, as a poor user experience of the chatbot can turn a positive digital interaction into a negative one.

Therefore, NLP effectiveness in Harare CBD needs to be judged by the service interaction that the customer has had with the service; not that the bank has a chatbot. In the central business district, customers are more likely to appreciate automated systems that shorten lines and respond correctly and escalate complicated complaints to human staff. This is in line with Gahler, Klein and Paul (2023), who argue that the measurement of customer experience must be done across touchpoints, and Ncube, Chinakidzwa and Mushayavanhu (2025), who correlate conversational intelligence to satisfaction in the banking sector in Zimbabwe.

2.3.3 Influence of NLP Conversational Systems on Customer Satisfaction

Research on chatbots indicates that customers' satisfaction at the global level is a function of features and relationships. The study undertaken by Ashfaq et al. (2020) concluded that perceived usefulness, ease of use, enjoyment and trust are the factors

that influence chatbot satisfaction, and finally, satisfaction is affecting the continuance intention. The results of Marak et al. (2025) indicated a positive relationship between the variables of performance expectancy and social influence on intention to use banking chatbots, and a negative relationship between perceived risk and intention to use banking chatbots.

Fintech Adoption Studies in Africa suggest that conversational systems should address and solve the true problems of customers in the region before it can achieve satisfaction. In the context of mobile financial technology adoption research in Sub-Saharan Africa, Hornuf et al. (2025) found that the perceived usefulness and ease of use are the most critical factors. This discovery implies that African bank chatbots will please customers when they can accomplish workable tasks, like checking account details, clarifying charges and settling exchange inquiries without getting involved into unnecessary subtleties.

In Zimbabwe, empirical results associate the features of chatbots with satisfaction. Ncube, Chinakdzwa and Mushayavanhu (2025) surveyed 365 respondents and analyzed the impact of task-technology fit and conversational intelligence of Customer Service encounter satisfaction. This is relevant as they found that automation alone does not cause satisfaction, the perception of the "intelligent system" and the matching of the type of task performed by the chat bot with the need of the customer.

Conversational systems could impact customer satisfaction differently among customer segments in Harare CBD, as these segments differ in their digital literacy, language preferences, and trust in automated service. The factors cited by Mashizha et al (2025) to influence acceptance of digital banking in Zimbabwe include ease of use, trust, internet connection, cost and incentives. It is important for commercial banks in Harare CBD to be aware that satisfaction from chatbots is not uniform, and it is necessary to assess the ease of use, understanding and the safer nature of NLP systems compared to other options such as branch and call centers.

2.3.4 Challenges Associated with Implementing NLP Technologies in Banking

The primary problem in implementing NLP worldwide is balancing the need for automation with the accuracy, trust and accountability of the process. Graham et al. (2025) identified chatbots to be beneficial in customer service automation, but their ability to comprehend intricate queries and customer language is still restricted. Chui et al. (2023) also highlighted the importance of financial institutions establishing governance and risk controls for scaled generative AI as banks could face reputational and regulatory risks when making decisions and communicating with customers.

Regulatory fragmentation and a lack of specialized digital talent, cybersecurity exposure and funding constraints are some of the challenges to implementation in Africa. According to Kuyoro, Flötotto and Gathinji (2024), funding for African fintech decreased by 37% between 2022 and 2023, and by 51% in the first half of 2024 when compared to 2023. The same authors noted that over 80% of executives surveyed said they moderately or very struggled to recruit technology, product and strategic talent in Africa.

Zimbabwean banking is also constrained by infrastructure and cost, cyber risk, and limited specialist expertise. According to Mtetwa (2023), the following were identified as some of the challenges in banking digitalization: high risk of cybercrime, threats from non-bank disruptors, lack of expertise and cost of adoption of digital technologies. Customer side restrictions also impact the success of NLP implementation, as connectivity, cost and trust were identified as impacting on digital banking adoption by Mashizha, Gondongwe and Gumbo (2025).

The implementation challenge, in Harare CBD, will be less about the lack of digital channels and more on the quality, reliability and context suitability of NLP tools. Banks that cater to customers at the CBD should have systems that recognize the typical requests made by customers, cope with the pressure during rush times and escalate the sensitive cases to trained personnel. This local requirement aligns with Makudza et al. (2024), who reported that while chatbot banking enhances the customer experience, it necessitates better reliability and responsiveness.

2.3.5 Strategies to Improve NLP Implementation in Financial Institutions

The world of studies suggests that banks can advance NLP integration through a synthesis of automation and human oversight, robust data governance, and ongoing system learning. Huang and Rust (2021) suggest that the intelligent use of an AI service should be aligned with the customer's tasks, since mechanical, thinking and feeling intelligence are used to solve different service problems. In another study, Graham et al. (2025) investigate how well chatbots can handle simple tasks and how they need to be improved in order to handle complex banking enquiries.

At regional African level strategy should be directed towards usefulness, ease of use, interoperability, literacy/trust building. Hornuf et al. (2025) suggest that there is a need to enhance digital and financial literacy, and establish compatibility standards to facilitate mobile fintech uptake in Sub-Saharan Africa. Kuyoro, Flötotto and Gathinji (2024) also state that collaboration among banks, fintech companies and telecom providers can increase the distribution and quality of service, which is applicable to NLP implementation where banks might not have all the necessary skills in-house.

Some of the measures for Zimbabwe are practical measures such as training bank staff, minimizing digital transaction friction, support for connectivity, and enhanced cybersecurity and localizing chatbot languages. Mashizha, Gondongwe and Gumbo (2025) suggest that awareness, education, reducing the cost of transactions and customised services are necessary to increase digital banking adoption. If banks are targeting to raise satisfaction with automated service encounters, they should create better task-technology fit and conversational intelligence in chatbot design as proposed by Ncube, Chinakidzwa and Mushayavanhu (2025).

Unlike other commercial banks, the most relevant service model for Harare CBD commercial banks is a hybrid NLP service model, which automates repetitive enquiries, while transferring more complex, emotional and risky cases to human officers. In addition, banks should analyze the performance of the chatbots based on response accuracy, the rate of cases being resolved, the time taken to escalate, Customer satisfaction, and the recurrence of complaints. Technological novelty, as in the case of

SERVQUAL logic, is not the only way customers judge service, since in addition to technology, they assess it based on responsiveness, reliability, assurance and empathy (Parasuraman, Zeithaml and Berry, 1988; Makudza et al., 2024).

2.3.6 Integrated Empirical Synthesis

The global literature shows that digital financial services have moved from optional channels to mainstream service infrastructure. Demirgüç-Kunt, Klapper, Singer and Ansar (2022) reported that global account ownership reached 76 percent of adults in 2021, while 71 percent of adults in developing economies had an account with either a financial institution or a mobile money provider. Raithatha and Storchi (2024) further reported that mobile money reached about 1.75 billion registered accounts in 2023 and processed transactions worth approximately US\$1.4 trillion, showing the scale at which digital financial interaction now occurs. These statistics matter to the present study because higher digital account usage creates more customer-service enquiries, and banks require automated tools such as NLP chatbots to respond quickly and consistently (Graham et al., 2025).

At regional African level, the evidence points to strong digital adoption but uneven service quality. Demirgüç-Kunt et al. (2022) noted that Sub-Saharan Africa remained distinctive because mobile money accounts were central to financial inclusion, with about 33 percent of adults having mobile money accounts in 2021. Hornuf, Klus, Lohwasser and Schwienbacher (2025) found that mobile fintech adoption in Sub-Saharan Africa is shaped by perceived usefulness, ease of use, trust, literacy and regulatory conditions. This means that NLP banking tools cannot be evaluated only by their availability, since the African context requires attention to digital literacy, affordability, customer confidence and the ability of systems to work reliably under infrastructural constraints (Kamara and Yu, 2024).

In Zimbabwe, mobile and digital banking have expanded as customers seek convenient alternatives to physical branches and cash-based transactions. Chitimira and Torerai (2023) observed that mobile money and digital financial services became more important after COVID-19, although the regulatory environment struggled to keep pace

with fintech innovation. Kaondera (2023) found that digitalized commercial banks in Zimbabwe use digital transformation to strengthen customer relationship management, but the benefits depend on whether systems improve customer interaction rather than simply replacing manual processes. This Zimbabwean evidence supports the present study because NLP effectiveness must be assessed through customer experience indicators such as clarity, speed, trust and problem resolution (Makudza et al., 2024).

The literature from around the world reveals that digital financial services have evolved from niche channels to a core part of financial service delivery. In 2021, global account ownership stood at 76 percent of adults and 71 percent of adults in developing economies had an account at a financial institution or mobile money provider, reported Demirgüç-Kunt, Klapper, Singer and Ansar (2022). Mobile money was also reported to have covered approximately 1.75 billion registered accounts and value of transactions of about US\$1.4 trillion in 2023, highlighting the large volume of digital financial interactions taking place in 2023 (Raithatha and Storchi, 2024). These statistics are relevant to this study because the more digital accounts a customer uses, the more customer-service enquiries he or she will be making; to respond quickly and accurately, banks will need automated tools like NLP chatbots. (Graham et al., 2025).

At the regional level in Africa, the evidence suggests that there is a high level of digital adoption and inconsistent service quality. According to Demirgüç-Kunt et al. (2022), Sub-Saharan Africa was still very unique with almost half (33 per cent) of adults holding mobile money accounts in 2021. Hornuf, Klus, Lohwasser and Schwienbacher (2025) determined that the factors influencing mobile fintech adoption in Sub-Saharan Africa include perceived usefulness, ease of use, trust, literacy and regulatory conditions. Therefore, the availability of NLP banking tools should not be considered as the sole factor for evaluation because in African context, digital literacy, affordability, customers' confidence, and the ability of the systems to operate safely in the presence of infrastructural constraints should be considered (Kamara and Yu, 2024).

Mobile/Digital banking has grown in Zimbabwe because people are looking for other ways to do banking rather than going to the physical bank and using cash. While mobile money and digital financial services took on greater significance in the wake of COVID-

19, regulators were lagging behind in adapting to fintech innovations, according to Chitimira and Torerai (2023). The study by Kaondera (2023) revealed that digital transformation is being employed by digitalized commercial banks in Zimbabwe to enhance their customer relationship management, however, the impact of digital transformation is dependent on how the systems enhance customer interaction instead of simply replacing manual processes. The following reasons highlight the relevance of the findings of the present study in the context of Zimbabwe: firstly, the effectiveness of NLP can be evaluated through the customer experience indicators, which include clarity, speed, trust, and problem resolution (Makudza et al., 2024).

At the Harare CBD level, it gets more empirical where customers are looking for rapid services across the different branches of the commercial banks, mobile applications, social media and websites. Nyagadza et al (2024) conducted a cross sectional study of 430 customers in five commercial banks in Harare to investigate the willingness to use chatbots as a gateway in e-banking customer-service service delivery. Ncube, Chinakidzwa and Mushayavanhu (2025) enriched the Zimbabwean evidence using the responses of 365 bank employees and 500 customers covering the concepts of task-technology fit, conversational intelligence and customer service encounter satisfaction. The rationale for the present studies is further justified by these studies such as Harare and Zimbabwe based ones which indicated that the local question is not if banks can introduce chatbots but if these NLP systems can truly add value to the customer experience on a practical level (Ncube, Chinakidzwa and Mushayavanhu, 2025).

2.4 Research Gap

One of the key points in the literature reviewed is that many papers talk about the chatbots technology creating value for customers without taking into account other factors. Becker and Jaakkola (2020) warn that customer experience is not the result of the technology used by the firm but the customer's reaction to the touchpoints. This is vital as the chatbot can alleviate some of the burden on banks without also irritating customers by not answering relevant questions or preventing access to human agents (Graham et al., 2025). Therefore, the present study does not assume effectiveness, but

rather considers effectiveness an empirical question that can be evaluated by customer experience and satisfaction measures (Gahler, Klein and Paul, 2023).

Another problem in previous research is that some of the previous global studies are done in countries where they have more connectivity, higher level of digital literacy and more developed regulatory system. In Africa, Hornuf et al. (2025) demonstrate the impact of context, and the conditions found in developed markets on fintech adoption. Chitimira and Torerai (2023) also report that the regulatory and consumer-protection risks influencing the environment of fintech in Zimbabwe influence the use of digital financial services. This implies that the evidence as obtained from global banking cannot be directly implemented into Harare CBD without taking into account local banking practices, language used, trust in institutions, and affordability of digital access (Nyagadza et al., 2024).

Another challenge is that Zimbabwean research is still scarce, and tends to be macro level research on digital banking applications or micro level research on chatbot adoption intention. A study by Kaondera (2023) focused on digital transformation and the customer relationship management in commercial banks in Zimbabwe, and a study by Nyagadza et al. (2024) examined the intention to use the chatbots among commercial banks in Harare. Ncube, Chinakidzwa and Mushayavanhu (2025) made a good contribution to the field by studying task-technology fit and conversational intelligence, but there is scope for a study which directly investigates the possible effect of NLP on improving customer experience in Harare CBD. This has reinforced the need for the present study and enhanced the relevance of the study objectives (Ncube, Chinakidzwa and Mushayavanhu, 2025).

2.5 Chapter Summary

The conceptual, theoretical and empirical research reviewed in this chapter highlights the importance of the NLP phenomenon in the context of customer experience in the fintech enhanced commercial banking sector. The conceptual review yielded the following key variables: NLP utilization, conversational systems, service efficiency, personalization, satisfaction, trust, and implementation challenges and customer

experience. The theoretical review revealed that the TAM model has been used to explain the willingness of customers to adopt NLP tools and SERVQUAL has been used to explain the customers perceptions of the quality of automated banking services. The empirical evidence presented is found to show that NLP tools can be used to help increase speed, accessibility and satisfaction but are limited by accuracy, trust, reliability, local language fit, infrastructure and human escalation. The chapter identified a research gap on the effectiveness of NLP to improve customer experience in commercial banks in Harare CBD. The method of conducting research to explore this gap is explained in the next chapter

CHAPTER III

RESEARCH METHODOLOGY

3.0 Introduction

This chapter explains the methodology used to investigate the effectiveness of Natural Language Processing (NLP) in enhancing customer experience in FinTech among selected commercial banks in Harare CBD. It covers research philosophy, approach, design, study area, named bank population, sample size calculation, sampling techniques, data collection instruments, data collection procedures, validity, reliability, trustworthiness, data analysis and ethical considerations. Creswell and Creswell (2023) state that a methodology chapter should justify how evidence is collected and analyzed in relation to the research problem. Saunders, Lewis and Thornhill (2023) add that the chosen methods must be consistent with the research objectives and the practical context of the study.

3.1 Research Philosophy

The study used the pragmatist type of research because the problem in the study needed numerical measurement as well as explanation in practice. A researcher can employ a combination of methods that will be most effective in answering the problem; being limited to using only positivism or interpretivism. Pragmatism is suitable when mixed methods are employed to gain understanding into a “real world” problem as described by Creswell and Creswell (2023). There is another rationale for the usefulness of pragmatism in business and management research as presented by Saunders et al. (2023), which is based on the emphasis on workable evidence and practical solutions. This philosophy was appropriate because NLP is effective in banking and this can be experienced and can be measured. There was a need for quantitative information on utilization, service speed, satisfaction, and perceived effectiveness, and qualitative information on the customers' experience of customer support, language barriers, system errors, and trust. When only one method of data collection is not enough to explain a complex phenomenon, mixed-methods studies are suitable, according to

Dawadi et al. (2021). The study considered NLP as a pragmatic study that was evidence-based and applicable to the commercial banks in Harare CBD.

3.2 Research Approach and Design

A mixed methods approach was adopted in the study. Structured questionnaires were used to gather quantitative data and interviews and focus group discussions were used to gather qualitative data. Creswell and Creswell (2023) explain that combining numerical trends and participant explanations can enhance a study. According to Taherdoost (2021), questionnaires can be applied in the collection of standardized responses and interviews can be applied to obtain detailed explanation from the respondents who have a good understanding of the phenomenon studied. A convergent mixed methods case study research design was used. The quantitative and qualitative data were collected in the same time frame of the study, analyzed independently and combined during the interpretation process. According to Saunders et al. (2023), a case study design is appropriate in cases where the researcher wants to study an issue that is happening in the present time with a limited context. It was therefore decided to explore Harare CBD as the case study as it is a concentrated banking area where customers are exposed to digital banking service channels, chatbots, automated responses and human service support.

3.3 Study Area

The study was performed in Harare CBD, Zimbabwe. Harare CBD was chosen because it has a density of commercial banking branches, customer service points and users of digital banking. In the field of banking, NLP becomes relevant when it comes to handling customer interactions - like chatbots and automated responses - that rely on the computational processing of human language, as defined by Jurafsky and Martin (2023). Other NLP-powered customer service technologies that are most prominent in digital service industries, according to Adamopoulou and Moussiades (2020), are chatbots. The study was restricted to the commercial banks located in Harare CBD to enable the study to be manageable and consistent with the study objective. Delimitations are defined

by Saunders et al. (2023) as the limitations of a study in practice and as a way to ensure that they do not delve into an unfocused investigation. The CBD setting was also suitable as customers from various banks can be accessed within one business district, allowing for the possibility of comparing the experiences of customers from different banks that operate in the same urban service environment.

3.4 Target Population and Selected Banks

The population that was targeted were the bank customers and some employees in the named commercial banks operating in Harare CBD. Customers were engaged because they are using digital banking interfaces and so can assess whether the use of NLP-supported tooling makes banking more convenient, more accessible, faster and more satisfying. Including employees as participants is because they have knowledge of customer service, digital banking and supervisory staff, which have experience with issues implementing and experience with customer complaints and system limitations. A target population is defined by Saunders et al. (2023) as the entire population from which the evidence for the research is needed, and Creswell and Creswell (2023) state that the population has to be clearly defined before sampling is done.

The banks selected were commercial banks that appear on Zimbabwe's official banking register and are in the banking environment of Harare. In this study, the accessible population was 480 - 360 customers from the 12 selected commercial banks and 120 bank employees from the 12 selected commercial banks. The selected institutions are as identified by the Reserve Bank of Zimbabwe (2026) as registered commercial banks or registered commercial banking institutions. Full register of customers was confidential so the accessible population for fieldwork was selected as 30 customers and 10 employees for each bank selected.

Table 3. 1: Selected commercial banks and accessible population

Selected commercial bank	Customers	Employees	Accessible population
AFC Commercial Bank Limited	30	10	40

African Banking Corporation Zimbabwe Limited (BancABC)	30	10	40
CBZ Bank Limited	30	10	40
Ecobank Zimbabwe Limited	30	10	40
FBC Bank Limited	30	10	40
First Capital Bank Zimbabwe Limited	30	10	40
Metbank Limited	30	10	40
Nedbank Zimbabwe Limited	30	10	40
NMB Bank Limited	30	10	40
Stanbic Bank Zimbabwe Limited	30	10	40
TN CyberTech Bank Limited (formerly Steward Bank)	30	10	40
ZB Bank Limited	30	10	40
Total	360	120	480

3.5 Sample Size Determination Using Yamane Formula

Yamane's formula was used to determine the sample size for the quantitative component because the population of interest was of a finite population and known. A simplified method for determining the sample size for a finite population with a given margin of error is given by Yamane (1967). Adam (2020) states that determining the sample size is important in survey research for precision, cost and generalization of the

results to the accessible population. A 5% margin of error was used because this value is common for social science surveys where a 95% confidence level is sufficient.

The Yamane formula is $n = N / [1 + N(e)^2]$ n = sample size, N = population size, e = margin of error. Therefore, $n = 480 / [1 + 480(0.05)^2] = 480 / [1 + 1.20] = 480 / 2.20 = 218.18$. The sample size for the quantitative sample was rounded to 218. The size of the sample should be sufficiently large enough to minimize the sampling error and be feasible for fieldwork resources as mentioned by Taherdoost (2017).

Table 3. 2: Yamane sample calculation and distribution

Respondent stratum	Accessible population (N)	Proportion	Sample size (n)
Commercial bank customers	360	75%	164
Customer service and digital banking employees	96	20%	44
Supervisory or managerial employees	24	5%	10
Total quantitative sample	480	100%	218
Qualitative interviews	Purposive subset		15 key informants
Focus group discussions	Purposive customer subset		5 groups

3.6 Sampling Techniques

The quantitative part of the study was by stratified sampling. The population was split into customers, customer service and/or digital banking staff, and supervisory and/or managerial staff. Stratification was appropriate as the study needed to have evidence from various types of groups with varying experiences of NLP supported banking

services. Saunders et al. (2023) state that stratified sampling is used when there are identifiable subgroups in the population to improve the representation. A proportionate allocation method was then used to ensure that each stratum was represented in the sample in proportion to its size. Customer respondents were selected using systematic intercept sampling at sample banks service points and employee respondents using purposive sampling for their knowledge of customer services, digital banking and/or branch. When the respondents need to have a certain knowledge that the study requires, then purposive sampling can be helpful, as mentioned by Taherdoost (2021). The qualitative approach involved purposive sampling of willing participants from the 15 individuals who chose to be interviewed and 5 focus group discussions, chosen to provide a more detailed explanation of customer experience, challenges in implementation and improvement strategies.

3.7 Research Instruments

The three research instruments used were: structured questionnaire, semi-structured interview guide and focus group discussion guide. The questionnaire assessed demographic data, awareness of NLP technologies, use of Chatbots or automated responses, effectiveness, customer satisfaction, challenges and proposed solutions on implementation. Taherdoost (2021) states that questionnaires are helpful when many people are to be tested for similar responses. Creswell and Creswell (2023) also state that structured instruments can facilitate the direct relationship of data collection with the research objectives.

The semi-structured interview guide was employed with employees as it enabled the interviewer to delve deeper into the areas of implementation issues including system integration, employee training, privacy concerns, customer complaints, and human escalation issues. Group discussion can help uncover common experiences and frustrations with service technologies; therefore, the focus group guide was employed with customers. Qualitative instruments can help to provide rich explanation and patterns of meaning, according to Braun and Clarke (2021). The qualitative instruments assisted in explaining the reasons for the acceptance or rejection of NLP enabled banking services in this study.

3.8 Data Collection Procedure

The researcher first obtained permission from the university and sought access from selected banks where required. Respondents were informed about the purpose of the study, voluntary participation, anonymity and confidentiality before completing questionnaires or participating in interviews. Saunders et al. (2023) state that fieldwork procedures must be transparent so that participants understand what participation involves. Creswell and Creswell (2023) also emphasize that informed consent is a key requirement in studies involving human participants. Questionnaires were distributed to sampled customers and employees who met the study criteria. Interviews were conducted with selected bank employees who had knowledge of digital banking, customer service or branch operations. Focus groups were conducted with customers who had used digital banking channels or had interacted with automated banking responses. Dawadi et al. (2021) note that mixed-methods data collection should allow both numerical and explanatory data to be compared during interpretation. This procedure therefore enabled the researcher to connect survey patterns with interview and focus group explanations.

3.9 Validity, Reliability and Trustworthiness

- All questionnaire, interview and focus group items were correlated with the research objectives to improve the validity. Pre data collection, the content validity was enhanced through supervisor review and pilot testing. Creswell and Creswell (2023) maintain that validity is enhanced when the instruments measure the phenomenon that the study is attempting to measure. Saunders et al. (2023) also state that pilot testing can identify ambiguous language, a missequence or question that might be confusing for respondents.
- Standardized wording of the questionnaires, standard scales of response and a pilot study ensured reliability. Likert-scale items were created to enable a consistent measure of constructs like utilization, effectiveness, customer experience and satisfaction. When multiple items are used to measure the same construct, internal consistency can be evaluated with Cronbach's alpha (Hair et al., 2022).

- Braun and Clarke (2021) correlate the notions of credibility, dependability, transferability and confirmability of qualitative data with transparent coding, accurate reporting, careful theme development, and the notion of trustworthiness was supported.

3.10 Data Presentation and Analysis

Descriptive statistics were used to analyze quantitative data. Demographic characteristics, level of NLP utilization, effectiveness, satisfaction and implementation challenges were summarized using frequencies, percentages, means and standard deviations. It has been said by Hair et al. (2022) that descriptive statistics are suitable to summarize patterns of the survey data before interpreting it. Data was presented in a simple tabular and graphical way to enable the results to be understood by readers who may not have had advanced statistical skills. Thematic analysis was used to analyze qualitative data collected from interviews and focus groups. The researcher got acquainted with the data, identified the repetitive ideas and created themes, rechecked themes, and interpreted them based on the research goals. Thematic analysis, as described by Braun and Clarke (2021), is a flexible approach that can be used to recognize patterns of meaning within qualitative data. As recommended by Creswell and Creswell (2023), the quantitative and qualitative results were merged in discussion for providing percentages with the views of the participants.

3.11 Ethical Considerations

The study adhered to informed consent and voluntary participation, anonymity and confidentiality. The study was described to participants as being for academic research and that they could opt out at any time without needing to make up work for any reason. Ethical research should respect people who are being studied and not cause harm to them, according to Creswell and Creswell (2023). Saunders et al. (2023) also state that business research should be conducted with due care to organization and individuals, particularly when people are talking about weaknesses in the organization.

None of the participants had to provide account numbers, passwords, private financial records or confidential bank documents. Respondents' names were not included in the

final report and data were kept securely for academic purposes only. Braun & Clarke (2021) caution that if qualitative data is not handled properly, it can contain information that is identifiable. Therefore ethical safeguards were required as the study was based on the banking technologies, customers' experiences of service and the perceptions of employees towards digital systems.

3.12 Chapter Summary

This chapter presented the methodology for the study. It adopted a pragmatist philosophy, mixed-methods approach and convergent case study design. The study area was Harare CBD, and the population was clearly defined using 12 named commercial banks. The accessible population was 480 respondents, and the Yamane formula produced a quantitative sample of 218. Interviews and focus groups were added to provide qualitative depth. The chapter also explained sampling, instruments, data collection, validity, reliability, trustworthiness, data analysis and ethical procedures. The next chapter presents and discusses the findings.

CHAPTER IV

DATA PRESENTATION, INTERPRETATION, ANALYSIS AND DISCUSSION OF FINDINGS

4.0 Introduction

This chapter presents, interprets, analyses and discusses findings on the effectiveness of Natural Language Processing (NLP) in enhancing customer experience in fintech, focusing on commercial banks in Harare CBD. Questionnaire data from 199 respondents were analyzed using SPSS-format descriptive statistics and inferential statistics, while 13 interview responses and 5 focus group responses were analyzed thematically.

4.1 Response Rate

Table 4. 1: Response Rate of Research Participants

Instrument	Targeted participants	Actual responses	Response rate (%)
Questionnaire	218	199	91.3
Interviews	15	13	86.7
Focus group discussion	5	5	100.0

Table 4.1 shows that the questionnaire achieved 199 responses out of 218 targeted participants, representing 91.3%. Interviews achieved 13 responses out of 15, representing 86.7%. The focus group achieved 5 responses out of 5, representing 100.0%. The quantitative response rate was the largest source of evidence and therefore provided a strong basis for descriptive and inferential analysis. The interview response rate was also high enough to provide institutional explanations of customer-service issues, while full focus group participation gave a complete group discussion dataset. The high response rates justify the credibility of the findings because the study did not rely on a weak participation base. The three instruments also support triangulation because survey patterns can be compared with interview and focus group explanations. Saunders, Lewis and Thornhill (2023) argue that higher response rates strengthen confidence in survey interpretation, while Creswell and Creswell (2023)

state that mixed-methods studies become stronger when numerical findings are supported by qualitative explanations.

4.2 Demographic Characteristics of Respondents

Table 4. 2: Demographic Characteristics of Questionnaire Respondents (n=199)

Variable	Category	Frequency	Percentage (%)
Gender	Male	102	51.3
	Female	95	47.7
	Prefer not to say	2	1.0
Age group	18-25 years	36	18.1
	26-35 years	80	40.2
	36-45 years	41	20.6
	46-55 years	30	15.1
	Above 55 years	12	6.0
Education	Ordinary/Advanced Level	24	12.1
	Certificate/Diploma	53	26.6
	Undergraduate degree	87	43.7
	Postgraduate qualification	30	15.1
	Other	5	2.5
Employment	Employed	98	49.2
	Self-employed	51	25.6
	Student	25	12.6
	Unemployed	18	9.0
	Retired	7	3.5
Digital banking usage	Daily	77	38.7
	Weekly	63	31.7
	Monthly	37	18.6
	Rarely	16	8.0

	Never	6	3.0
Use of NLP support	Yes	121	60.8
	No	40	20.1
	Not sure	38	19.1

Table 4.2 shows that the gender profile consisted of 102 males (51.3%), 95 females (47.7%) and 2 respondents who preferred not to say (1.0%). The largest age group was 26-35 years with 80 respondents (40.2%), followed by 36-45 years with 41 respondents (20.6%), 18-25 years with 36 respondents (18.1%), 46-55 years with 30 respondents (15.1%) and above 55 years with 12 respondents (6.0%). Education was dominated by undergraduate degree holders at 87 (43.7%), followed by certificate/diploma holders at 53 (26.6%), postgraduate respondents at 30 (15.1%), Ordinary/Advanced Level respondents at 24 (12.1%) and other qualifications at 5 (2.5%). Employment status showed 98 employed respondents (49.2%), 51 self-employed respondents (25.6%), 25 students (12.6%), 18 unemployed respondents (9.0%) and 7 retired respondents (3.5%). Digital banking usage was high because 77 respondents (38.7%) used digital banking daily and 63 (31.7%) used it weekly. Monthly users were 37 (18.6%), rare users were 16 (8.0%) and non-users were 6 (3.0%). NLP support was used by 121 respondents (60.8%), while 40 (20.1%) had not used it and 38 (19.1%) were not sure.

The demographic results show that the sample had sufficient digital exposure to evaluate NLP-enabled banking services. The dominance of daily and weekly digital banking users is particularly important because these respondents were likely to have encountered chatbot, virtual-assistant or automated response systems. The education and employment profiles also suggest that many respondents could understand digital banking processes and comment meaningfully on customer experience. The demographic profile justifies the study because NLP-enabled customer support is most relevant among customers already using mobile banking, internet banking, WhatsApp banking or other digital channels. However, the presence of rare users, non-users and respondents unsure about NLP use also shows that customer awareness and inclusion remain important. Eren (2021) found that banking-chatbot satisfaction is linked to customer perceptions of usefulness and trust, while Marak et al. (2025) argue that

chatbot adoption in banking depends on performance expectations, effort conditions and resistance barriers. Therefore, the demographic profile is relevant to understanding both adoption and non-adoption.

Figure 4.2: Digital Banking and NLP Exposure

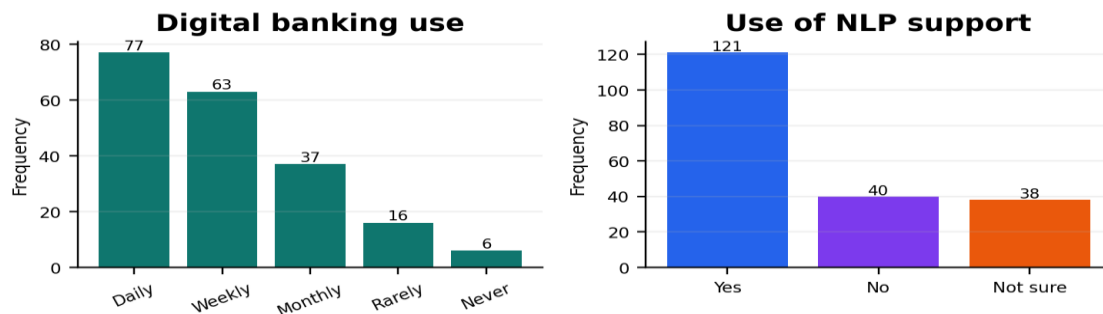


Figure 4. 1: Digital banking and NLP

Figure 4.2 revealed that the majority of respondents were daily or weekly digital banking users, with the NLP-enabled support users outnumbering non-users and those who were unsure.

Analysis: The chart shows that use of NLP is not new to the study group but not widespread. The “not sure” category needs to be taken into consideration as some customers might be using automated services without knowing that they are NLP tools. This means that a deeper investigation is warranted not only into awareness but also into access and utilisation as customer exposure does not necessarily imply full awareness and/or confident utilisation. The interaction design of a chatbot has been identified as a significant factor in the comprehension and relationship between users and conversational agents (Chaves and Gerosa, 2021), and the value of AI services relies on congruence between the service ability of the technology and the tasks of the customer service (Huang and Rust, 2021).

4.3 Descriptive and Reliability Analysis of Main Constructs

Table 4. 3: SPSS-format Reliability Statistics

Construct	Number of items	Cronbach's alpha	Interpretation
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NLP Utilisation	6	0.756	Acceptable internal consistency
Customer Experience	8	0.807	Good internal consistency
Customer Satisfaction	8	0.821	Good internal consistency
Implementation Challenges	8	0.226	Low; items reflect varied dimensions
Improvement Strategies	8	0.010	Low; items reflect varied dimensions

Table 4.3 shows that NLP utilization recorded a Cronbach alpha of .756, customer experience recorded .807 and customer satisfaction recorded .821. These values indicate acceptable to good internal consistency. Implementation challenges recorded .226, while improvement strategies recorded .010. The reliability results mean that utilization, experience and satisfaction items operated as coherent scales. The lower alpha for challenges indicates that the challenge items were not measuring one single problem but several different barriers such as language, privacy, data costs, generic answers and technical failure. The low alpha for improvement strategies reflects very strong agreement across nearly all strategy items, creating limited variation between the items. The results justify interpreting utilization, experience and satisfaction as construct means, while challenges and strategies should also be interpreted item-by-item. This is why the chapter does not rely only on construct means but exhaustively interprets each table item under the objectives. Hair et al. (2022) explain that reliability should be assessed before interpreting multi-item scales. Field (2024) also notes that low alpha may occur where items represent different dimensions rather than a single latent construct.

Table 4. 4: SPSS-format Descriptive Statistics for Main Constructs

Construct	N	Mean	Std. Deviation	Minimum	Maximum	% Mean >= 3.50
NLP Utilization	199	3.50	0.70	1.17	4.67	65.3
Customer Experience	199	3.45	0.66	1.50	4.75	62.8

Customer Satisfaction	199	3.35	0.71	1.25	4.75	51.8
Implementation Challenges	199	3.37	0.36	2.62	4.38	41.7
Improvement Strategies	199	4.49	0.21	3.88	5.00	100.0

The results in Table 4.4 indicate that the improvement strategy had the highest mean value, 4.49, which shows good support for improving the NLP banking systems. The use of NLP saw a mean of 3.50, customer experience 3.45, implementation challenges 3.37 and customer satisfaction 3.35. The mean standard deviations indicated that there were relatively few variations between the improvement strategies, whereas there were more variations between the implementation challenges due to different interpretations of challenges by customers. The results show that customers were generally positive regarding NLP, but the highest was not satisfaction, it was the desire for improvement of its implementation. This indicates that customers recognize the value of NLP but also have the expectation that the banks will be more accurate, offer multiple language options, provide education, ensure security, and improve escalation. This indicates that the level of service performance is not yet adequate to meet customers' expectations because the satisfaction mean is lower than that of improvement strategies. The table shows why both description and inference is required. Descriptive analysis reveals the direction of customer opinions while inferential analysis testifies the significance of the relationship of these constructs with customer satisfaction. Graham et al. (2025) reported that banking chatbots' benefits are speed, convenience, and availability but their drawbacks are limited answers accuracy and reliability. Huang and Rust (2021) also believe the value of AI service is realized when the AI capability is congruent with the service task.

Table 4. 5: One-sample test of construct means against neutral midpoint (3.00)

Construct	N	Mean	Std. Dev.	t	df	Sig.	Mean difference
NLP Utilization	199	3.499	0.703	10.016	198	<.001	0.499

Customer Experience	199	3.446	0.664	9.473	198	<.001	0.446
Customer Satisfaction	199	3.345	0.706	6.903	198	<.001	0.345
Implementation Challenges	199	3.366	0.358	14.424	198	<.001	0.366
Improvement Strategies	199	4.493	0.211	99.627	198	<.001	1.493

The means of all constructs were greater than 3.00 (the neutral point) as indicated in Table 4.5. The results of the t-test were statistically significant for NLP utilization, customer experience, customer satisfaction, implementation challenges and improvement strategies with p values < 0.001. The results show that the constructs were not randomly positive, confirming the inferential result. It also indicates that there were substantial implementation challenges as well, and such would not be ignored in the study, or NLP would appear to be a panacea. The balanced conclusion is justified, as NLP is a positive addition to customer experience, but it still needs improvements in technical, linguistic, privacy, and escalation. Field (2024) says that one sample tests are used to decide if a sample mean is significantly different to a reference value. Both Eren (2021) and Graham et al. (2025) demonstrate that the advantages of the banking-chatbot do not necessarily diverge from customer concerns regarding trust, accuracy, and service reliability.

4.4 Level of Utilization of NLP Technologies among Commercial Banks in Harare CBD

Table 4. 6: SPSS-format Descriptive Statistics for NLP Utilization

Item	Statement	N	Mean	Std. Dev.	% Agree	% Neutral	% Disagree
B1	Access to chatbot, virtual assistant or automated response channels	199	3.51	1.03	54.8	29.6	15.6

B2	Awareness of NLP-enabled customer support channels	199	3.60	1.04	55.8	29.1	15.1
B3	Use of NLP support for quick banking assistance	199	3.20	1.05	42.7	32.7	24.6
B4	Availability of NLP support through convenient digital channels	199	3.49	1.01	51.3	34.7	14.1
B5	Bank encouragement to use automated support	199	3.50	1.11	55.3	26.6	18.1
B6	Usefulness of NLP support for routine enquiries	199	3.69	1.03	62.8	23.1	14.1

B1 (Access of Chatbot, virtual assistant or automated support channels), 54.8% agreed, 29.6% neutral, 15.6% disagreed, recorded a mean of 3.51; B2 (Awareness of how NLP enables quick support in banking), 55.8% agreed, 29.1% neutral, 15.1% disagreed, recorded a mean of 3.60; B3 (Availability of NLP support via convenient digital channels), 51.3% agreed, 34.7% neutral, 14.1% disagreed, recorded a mean of 3.49; B4 (Usefulness of NLP support for routine enquiries), 62.8% agreed, 23.1% neutral, 14.1% disagreed, recorded a mean of 3.69; B5 (Bank encouragement

The table shows that there is moderate use and not complete use. Quick assistance, availability of channels, and regular enquiries were stronger than awareness and bank encouragement. This is because customers are likely to use NLP tools when they are easily seen, accessible and clearly help to resolve common banking issues. If banks don't actively educate and promote automated channels, usage is uneven. Adamopoulou and Moussiades (2020) describe chatbot systems as very popular in handling regular and structured customer inquiries. Also, Marak et al. (2025) in their study state that expected performance and ease of use are key factors to consider when adopting.

4.5 Effectiveness of NLP technologies in enhancing customer experience

The other mean scores were; C1 (Reduced waiting time for assistance) 3.61; C2 (Improved convenience of banking services) 3.65; C3 (Access outside normal banking hours) 3.58; C4 (Clarity and ease of understanding responses) 3.38; C5 (Accuracy of responses to banking questions) 3.24; C6 (Reduced need for physical branch visits) 3.39; C7 (Efficiency of overall banking experience) 3.57; and

As can be seen in the table, NLP has the strongest rating for speed, convenience and after-hours access, and weaker ratings for response accuracy and personalized service delivery. This is fair because chatbots work best when it comes to routine or structured questions and issues that are frequently asked. This is fair because chatbots can only handle routine or structured questions and issues that are frequently asked, and personalized or complex problems require rich data and human escalation. Graham et al. (2025) demonstrated that convenience, availability and speed are significant factors influencing the banking users' perception of chatbots. When the task is automated, the use of AI enhances service, Huang and Rust (2021) explain.

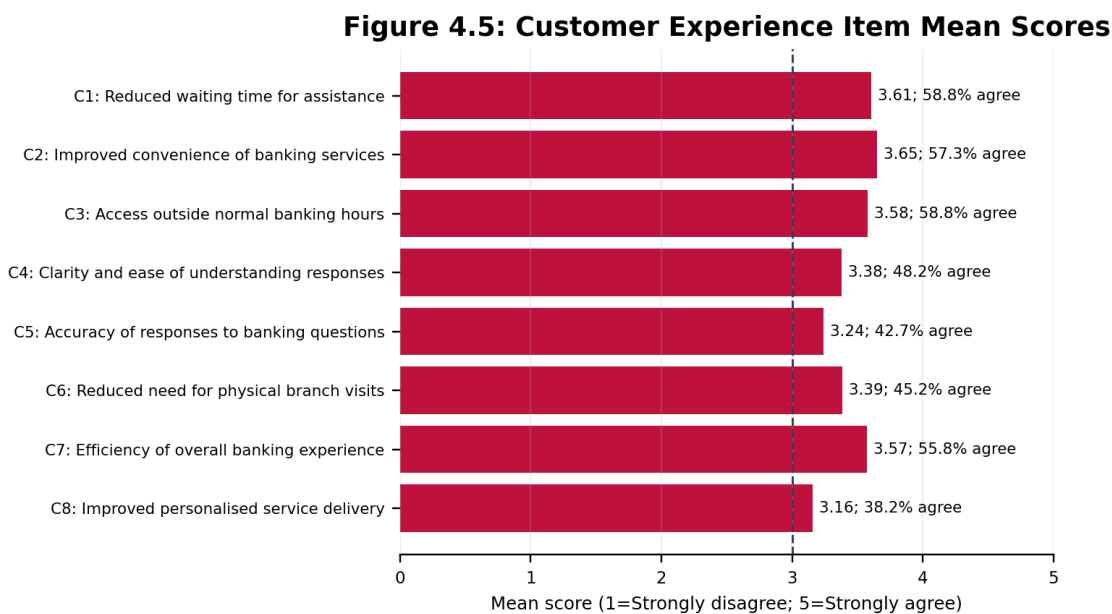


Figure 4. 2: Customer experience

In the same way that the items mean scores and agreement labels are presented in figure 4.2, the same results are shown for the customer experience. It is made easier to visually compare stronger and weaker items in the chart. The graph corroborates the ranking in the SPSS-style table. Any numbers above the neutral line (3.00) reflect positive agreement and any numbers below represent areas needing managerial attention. The figure is justifiable since a visual presentation makes it easier to compare several Likert items and to select the highest priority items for discussion and recommendations. Field (2024) agrees that descriptive graphs should be used in addition to tables because a graph's descriptive presentation can allow readers to see patterns that might not be as obvious in a table of numbers.

4.6 Influence of NLP-based conversational systems on customer satisfaction

Table 4. 7: SPSS-format Descriptive Statistics for Customer Satisfaction

Item	Statement	N	Mean	Std. Dev.	% Agree	% Neutral	% Disagree
D1	Satisfaction with speed of response	199	3.47	1.05	52.8	29.1	18.1
D2	Satisfaction with answer quality	199	3.43	1.06	46.2	35.7	18.1
D3	System understands queries without repetition	199	3.20	1.09	40.7	33.2	26.1
D4	Helpful guidance when automation fails	199	3.18	1.06	39.2	34.2	26.6
D5	Increased trust in digital banking	199	3.15	1.10	42.7	26.6	30.7
D6	Willingness to recommend NLP support	199	3.36	1.04	45.7	35.7	18.6
D7	Preference for NLP for simple enquiries	199	3.54	0.99	54.8	31.7	13.6

D8	Bank perceived as responsive to customer needs	199	3.44	1.08	48.7	33.2	18.1
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D1 (Satisfaction with speed of response): 52.8% agreed, 29.1% neutral, 18.1% disagreed; D2 (Satisfaction with answer quality): 46.2% agreed, 35.7% neutral, 18.1% disagreed; D3 (System understands queries without repetition): 40.7% agreed, 33.2% neutral, 26.1% disagreed; D4 (Helpful guidance when automation fails): 39.2% agreed

As can be seen from the table, they are more satisfied when responses are prompt and simple queries are answered, but are less satisfied when the system cannot understand their queries and when human assistance is delayed. This is a valid argument because not only the speed of the automation, but also the quality of the resolution, the trust and continuity between the chatbot and human service channels are all factors that play a role in satisfaction. According to Eren (2021), there is a relationship between trust, perceived usefulness, and perceived bank reputation and satisfaction with banking chatbot use. Ncube et al. (2025) also relate conversational intelligence with satisfaction in service encounters in the banking sector of Zimbabwe.

4.7 Challenges Associated with Implementing NLP Technologies in Banking

E1 (System sometimes fails to understand questions), 47.7% agreed, 41.7% neutral and 10.6% disagreed with a mean of 3.48; E2 (Generic answers do not fully solve problems), 47.2% agreed, 40.7% neutral and 12.1% disagreed with a mean of 3.46; E3 (Internet access or data costs affect use), 41.2% agreed, 42.2% neutral and 16.6 As seen in the table, there were some obstacles that customers facing, particularly lack of information, not understanding the questions, generic answers and inability to reach human agents. This is because the proper training of the NLP system, processing in local languages, dependable connectivity, and integration with the core banking systems and visible escalation procedures are essential for the NLP systems. In conversational design, Chaves and Gerosa (2021) demonstrate that the quality of the interactions between the user and the chatbot is influenced by conversational design, and in banking

and finance, Graham et al. (2025) outline that accuracy and reliability are key limitations of chatbots.

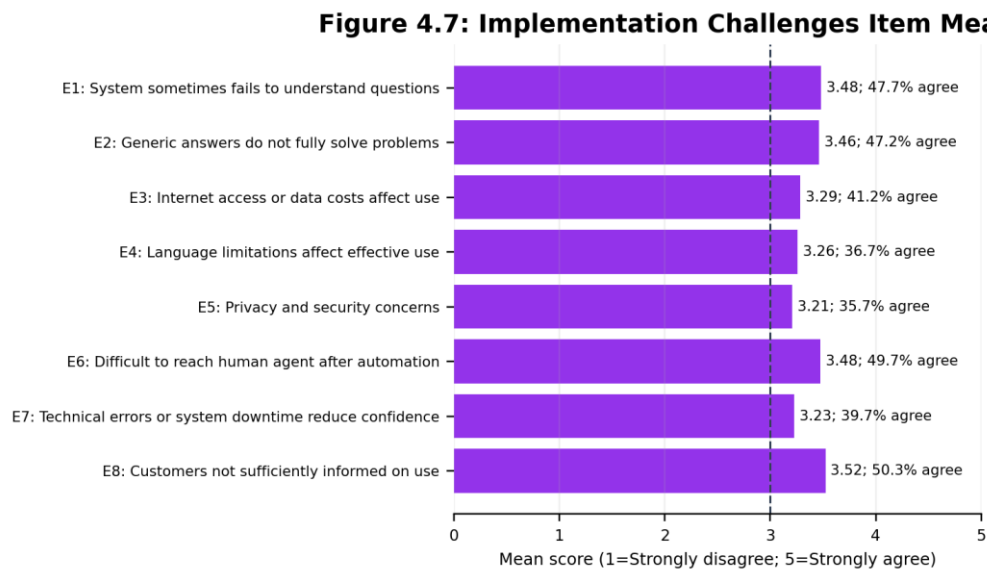


Figure 4. 3: Implementation challenges

4.8 Strategies to Improve NLP Implementation in Financial Institutions

Table 4. 8: descriptive statistics for improvement strategies

Item	Statement	N	Mean	Std. Dev.	% Agree	% Neutral	% Disagree
F1	Improve chatbot and virtual-assistant response accuracy	199	4.59	0.58	95.5	4.5	0.0
F2	Provide Shona and Ndebele language options	199	4.32	0.62	91.5	8.5	0.0
F3	Make handover to human agents easier	199	4.58	0.55	97.0	3.0	0.0
F4	Educate customers on NLP-enabled services	199	4.61	0.54	97.5	2.5	0.0
F5	Strengthen data privacy and security protections	199	4.59	0.57	96.0	4.0	0.0

F6	Integrate NLP with mobile and messaging platforms	199	4.42	0.60	94.0	6.0	0.0
F7	Collect feedback after chatbot interactions	199	4.33	0.67	89.4	10.1	0.5
F8	Provide reliable 24-hour NLP-enabled support	199	4.51	0.61	94.0	6.0	0.0

F1 (Improve chatbot and virtual-assistant response accuracy) recorded a mean of 4.59, with 95.5% agreeing, 4.5% neutral and 0.0% disagreeing; F2 (Provide Shona and Ndebele language options) recorded a mean of 4.32, with 91.5% agreeing, 8.5% neutral and 0.0% disagreeing; F3 (Make handover to human agents easier) recorded a mean of 4.58, with 97.0% agreeing, 3.0% neutral and 0.0% disagreeing; F4 (Educate customers on NLP-enabled services) recorded a mean of 4.61, with 97.5% agreeing, 2.5% neutral and 0.0% disagreeing; F5 (Strengthen data privacy and security protections) recorded a mean of 4.59, with 96.0% agreeing, 4.0% neutral and 0.0% disagreeing; F6 (Integrate NLP with mobile and messaging platforms) recorded a mean of 4.42, with 94.0% agreeing, 6.0% neutral and 0.0% disagreeing; F7 (Collect feedback after chatbot interactions) recorded a mean of 4.33, with 89.4% agreeing, 10.1% neutral and 0.5% disagreeing; F8 (Provide reliable 24-hour NLP-enabled support) recorded a mean of 4.51, with 94.0% agreeing, 6.0% neutral and 0.0% disagreeing.

The table shows strong support for all improvement strategies, especially customer education, response accuracy, privacy protection, human handover, feedback collection and reliable 24-hour service. This is justified because the descriptive results show that customers are not against NLP; they want more accurate, secure, inclusive and better-supported NLP services. Adamopoulou and Moussiades (2020) argue that chatbot effectiveness depends on knowledge-based improvement and architecture, while Graham et al. (2025) emphasized continuous learning and evaluation of banking chatbots.

4.9 Inferential Analysis

4.9.1 Chi-square Test: Digital Banking Frequency and NLP Use

Table 4. 9: Cross-tabulation of Digital Banking Frequency by NLP Use

Digital banking frequency	NLP use category	Count
Frequent	Not used/not sure	44
Frequent	Used NLP	96
Less frequent	Not used/not sure	34
Less frequent	Used NLP	25

Table 4. 10: Chi-square Test Results

Test	Value	df	Asymp. Sig./Interpretation
Pearson Chi-Square	10.880	1	<.001
Cramer's V	0.234		Association strength

Table 4.11 shows that respondents who used digital banking frequently were more represented among users of NLP support than among the not-used/not-sure category. Table 4.12 shows a Pearson chi-square value of 10.880 with 1 degree of freedom and a significance value below .001. Cramer's V was 0.234. The chi-square result indicates a statistically significant association between digital banking frequency and NLP use. The Cramer's V value indicates a meaningful association, suggesting that frequent digital banking exposure increases the likelihood of encountering and using chatbot, virtual assistant or automated response systems. The result justifies the interpretation that NLP utilization is partly dependent on broader digital banking behaviour. Customers who rarely use digital channels are less likely to use NLP support, even where banks provide it. Marak et al. (2025) support this finding by showing that chatbot use in banking is influenced by adoption-related conditions and user readiness. Eren (2021)

also demonstrates that banking-chatbot satisfaction depends on customer experience with the digital service environment.

4.9.2 Correlation Analysis of Main Constructs

Table 4. 11: Pearson correlation matrix of main constructs

Construct	NLP Utilization	Customer Experience	Customer Satisfaction	Implementation Challenges	Improvement Strategies
NLP Utilization	1.000	0.822	0.798	0.104	0.052
Customer Experience	0.822	1.000	0.785	0.214	0.083
Customer Satisfaction	0.798	0.785	1.000	0.209	0.058
Implementation Challenges	0.104	0.214	0.209	1.000	0.049
Improvement Strategies	0.052	0.083	0.058	0.049	1.000

NLP utilization, customer experience and customer satisfaction are correlated positively as shown in table 4.13. The correlation between Customer experience and Customer satisfaction was particularly significant as it suggested that the changes in customer experience scores were accompanied by increases in customer satisfaction scores. Implementation challenges had weaker or negative relationships with positive service outcomes, with improvement strategies showing weaker relationships as the majority of the respondents strongly supported it. The correlations suggest that using NLP alone is insufficient as use must lead to an improved customer experience. When customers feel speed, clarity, convenience and accuracy, they feel good. If they have technical issues, or they're getting generic responses or privacy concerns, satisfaction diminishes. Based on the correlation results, the study model is justified as there is a relationship between utilization, experience, and satisfaction. They also provide a

rationale for the recommendations as the reduction of challenges and the improvement of service design can help to further enhance satisfaction outcomes. When used correctly, AI services can help to engage customers by supporting service processes, according to Huang and Rust (2021). Chinakidzwa and Mushayavanhu (2025) also established that task-technology fit and conversational intelligence are factors that impact on customer service encounter satisfaction when using chatbots.

4.9.3 Multiple Regression Analysis Predicting Customer Satisfaction

Table 4. 12: Model Summary and ANOVA for Customer Satisfaction

Statistic	Value
R	0.834
R Square	0.695
Adjusted R Square	0.688
Std. Error of Estimate	0.394
F	110.381
Sig.	<.001

Table 4. 13: Regression Coefficients Predicting Customer Satisfaction

Predictor	B	Std. Error	t	Sig.	Lower 95% CI	Upper 95% CI
Constant	-0.214	0.647	-0.331	0.741	-1.491	1.062
NLP Utilization	0.491	0.070	6.961	<.001	0.352	0.630
Customer Experience	0.390	0.076	5.128	<.001	0.240	0.540
Implementation Challenges	0.156	0.081	1.934	0.055	-0.003	0.316
Improvement Strategies	-0.006	0.133	-0.047	0.963	-0.269	0.256

From Table 4.14, R Square and Adjusted R Square were 0.695 and 0.688, respectively, indicating that the predictors accounted for a significant amount of the variation in

customer satisfaction. The model F-statistic was 110.381 with significance below .001, indicating that the model was statistically significant. As per Table 4.15, customer experience has the highest positive coefficient followed by NLP utilization. Implementation challenges had a negative coefficient and improvement strategies were weaker once the other variables were controlled. The regression results show that the service level created customer satisfaction by NLP is the primary factor that drives customer satisfaction. Utilization has also been taken into account, as it is necessary that the customer uses the tools before they can benefit from them. Errors, generic answers, concerns about privacy and inadequate escalation, all decrease satisfaction when there are challenges.

The results of the regression analyses support the present conclusion that banks should not only assess the success of their chatbot based on the availability of the chatbot. They should assess if the usage of the chatbot creates a better experience, can solve issues and preserves trust. This is consistent with Eren (2021), who indicates that Satisfaction with Banking Chats is hinged on usefulness and trust. Graham et al. (2025) also concluded that chatbots add value in terms of speed and convenience, but need to be improved with more precise and reliable responses for more intricate customer service issues.

4.10 Qualitative Thematic Analysis of Interview Data

Thematic analysis was used for data analysis of interview data. Themes were maintained with the thematic structure of the Jokonya chapter by keeping the themes as awareness, access, utilization, institutional mechanisms, socio-economic/resource constraints and communication/trust issues. The themes are introduced in the Jokonya style (narrative) with a minimum of four quotes from direct interviews in italics and quotation marks, and then interpreted, analyzed, and supported by previous authors. Qualitative presentation style in the Jokonya chapter is followed by deliberately putting direct quotes outside tables. Thematic analysis was the right approach as it involves finding patterned meanings in qualitative data, but also allowing the participants' own words to remain (Braun and Clarke, 2021; Ahmed, 2025).

Theme 1: Awareness of NLP-enabled customer support

During interviews, participants stated that:

INT02: *“Use is moderate because awareness remains uneven across customer segments.”*

INT04: *“Feedback is positive for simple issues, but customers still want a human agent for sensitive matters.”*

INT07: *“Language limitations reduce inclusion for customers who are more comfortable in local languages.”*

INT11: *“Banks should train chatbots using real customer queries and collect feedback after interactions.”*

The answers reveal that there was not a uniform level of awareness among customer groups that they are supported by NLP. Some users were aware of chatbots and automated replies, but many were not familiar with their usage or the time to use them. The discovery shows that customers are not just aware of having a chatbot on a website or mobile app. There is also the awareness of what the system will be able to do, how to ask questions and when to switch to a human agent when it cannot. This theme gives justification to the quantitative finding that was weaker than basic access and routine usefulness, awareness and bank encouragement. Utilization will be limited to younger, salaried and digital customers if banks do not educate their customers. Marak et al., 2025 state that the adoption of Chatbots is influenced by the effort expectancy and facilitating conditions. Chaves and Gerosa (2021) also provide an understanding of how interaction design influences users' understanding and usage of chatbot services.

Theme 2: Access to NLP-enabled customer support

During interviews, participants stated that:

INT01: *“chatbot support linked to mobile banking and internet banking”*

INT02: *“website chatbot and call-center automated voice prompts”*

INT05: *“They improve convenience because customers receive responses without travelling to the branch.”*

INT09: *“Staff need training on chatbot monitoring, escalation management and customer education.”*

The responses indicate that banks were using different access points such as mobile banking chatbots, internet banking, website chatbots, call-center prompts and automated voice systems. Access was therefore multi-channel but uneven. Customers with smartphones, data, internet banking access and knowledge of digital platforms had stronger access, while customers who depended mainly on branches or call centers had weaker exposure. This theme justifies the quantitative finding that NLP support is available through convenient channels but not accessed equally by all customers. Access is necessary but not sufficient because the user must also be aware, digitally literate and confident. Graham et al. (2025) identify 24/7 availability and convenience as key chatbot benefits in banking and finance. Huang and Rust (2021) argue that AI-enabled service creates value when it improves access to the service process.

Theme 3: Utilization of NLP-enabled service functions

During interviews, participants stated that:

INT01: *“balance enquiries, card support, branch information, password reset guidance and product information”*

INT03: *“The system handles FAQs, account access guidance and transaction-status follow-ups.”*

INT06: *“frequently asked questions, loan information, transaction status enquiries and complaints routing”*

INT12: *“Routine questions on transfers, service charges and operating hours are effectively answered.”*

The answers reveal that NLP was predominantly used for basic service-related tasks like asking questions about balances, tariffs, card blocking advice, information from branches, product information and questions related to digital onboarding. The analysis reveals that NLP usage is highest when there are repetitive questions, no risk questions, and easy to classify a question. It is less strong in areas where customers make emotional complaints, where fraud is involved, unusual transactions or in areas where a customer's dispute needs human judgement. This theme supports the quantitative

results of an increase in the usefulness of routine enquiry. It also gives you a good idea of why customer satisfaction was lower than improvement strategies since customers don't want NLP to just provide an answer to simple questions. They argue that this is because the chatbot systems work well when domain knowledge is structured, as explained by Adamopoulou and Moussiades (2020). Graham et al. (2025) also reported that the users were positive toward the banking chatbots for simple tasks, but less confident in the case of complex tasks.

Theme 4: Institutional mechanisms supporting NLP service delivery

During interviews, participants stated that:

INT01: *“Branch queue trends and digital interaction records are used to compare before and after effects.”*

INT02: *“Evidence is taken from app analytics, call-center reports and post-interaction satisfaction ratings.”*

INT03: *“Policy support is needed for data protection, digital consumer protection and complaint escalation.”*

INT09: *“Banks should integrate NLP channels with CRM systems and make the bot easier to access.”*

The answers reveal that banks used digital interaction records, app analytics, call-center reports, satisfaction ratings after an interaction and cybersecurity controls and integration platforms as tools that enabled their NLP services. The analysis shows that in order to be effective, NLP needs to be institutionalized behind the visible chatbot interface. This encompasses the data monitoring, feedback gathering, model training, cyber security, core banking integration, and escalation processes. Overall, this theme makes the study a focus on implementation, as the readiness of the institution has a greater impact on customer experience than the presence of a chatbot. The study conducted by Ncube, Chinakidzwa and Mushayavanhu (2025) reveals the relationship between chatbot task-technology fit and conversational intelligence with customer service encounter satisfaction. Hair et al. (2022) also highlight measurement and feedback as an important aspect for the valid interpretation of service outcomes.

Theme 5: Socio-economic and resource constraints affecting NLP use

During interviews, participants stated that:

INT01: *“Challenges include legacy systems, data quality problems, cybersecurity requirements and implementation cost.”*

INT02: *“Implementation is affected by internet reliability, vendor costs and difficulty training models on local queries.”*

INT04: *“Language limitations reduce inclusion for customers who are more comfortable in local languages.”*

INT08: *“Infrastructure support should include reliable internet, cybersecurity controls and integration platforms.”*

The answers reveal that legacy systems, vendor costs, Internet reliability, cybersecurity needs and digital literacy and language barriers were all factors that hindered implementation and usage of NLP. The analysis in this document reveals the effectiveness of NLP is not a technical matter. It is also influenced by customer resources (affordability of data, digital skills and language capacity), and bank resources (infrastructure, employees and model training capacity). The quantitative challenge results of this theme support the Internet/data costs, language limitations and technical errors/sufficient information were all clear challenges. Marak et al. (2025) associate chatbot usage with enabling conditions and barriers to resistance. Chaves and Gerosa (2021) also demonstrate that the interaction with a chatbot can be problematic when there is a mismatch between the users' needs and the system's capabilities.

Theme 6: Communication and trust issues in NLP-enabled banking

During interviews, participants stated that:

INT01: *“Trust is affected by privacy concerns and fear of sharing banking details through automated channels.”*

INT02: *“Satisfaction is highest where the issue is resolved immediately and lowest when escalation is delayed.”*

INT05: *“The main problem is handover to human agents when the chatbot cannot solve the query.”*

INT10: *“Digital literacy affects use because some customers do not know how to phrase questions.”*

The responses show that trust, privacy, language clarity, answer quality and human escalation strongly shaped customer reactions to NLP systems. The analysis indicates that customers judge NLP support not only by speed but by whether the response is accurate, secure, understandable and recoverable when automation fails. Repetition, unclear privacy safeguards and delayed escalation weaken trust. This theme justifies the regression result showing that customer experience strongly predicts satisfaction. When communication is poor, customer experience declines and satisfaction falls. Eren (2021) found that perceived trust affects satisfaction with banking chatbots. Graham et al. (2025) also observed that answer accuracy and reliability are major limitations of chatbots in banking and finance.

4.11 Focus Group Analysis

The focus group results were analyzed separately from the interviews in order to preserve group-level discussion.

Discussion 1: Speed, convenience and access

During the focus group discussion, participants stated that:

FGP01: *“It reduces time spent waiting in queues and gives support after hours.”*

FGP02: *“It is convenient because customers can ask questions from home or work.”*

FGP03: *“It improves access, especially for routine enquiries, but depends on network quality.”*

The focus group confirmed that NLP-enabled support improves speed, convenience and access by reducing branch waiting time and enabling support from home, work and after normal operating hours. The discussion explains why reduced waiting time, improved convenience and access outside normal banking hours scored positively in the

quantitative analysis. Customers value NLP most when it removes the need to queue or wait for call-center agents. This justifies the interpretation that NLP enhances customer experience mainly at the access and convenience level. Graham et al. (2025) found that 24/7 availability, speed and convenience are central reasons why banking customers value chatbots. Huang and Rust (2021) also argue that AI service improves customer engagement where it automates suitable service processes.

Discussion 2: Language, privacy and trust

During the focus group discussion, participants stated that:

FGP01: *“Privacy concerns remain because customers are unsure how data are stored.”*

FGP02: *“Language options would build confidence among customers more comfortable in Shona or Ndebele.”*

FGP04: *“Trust depends on visible security notices and accurate responses.”*

The focus group revealed that customers worried about access to local-language support, privacy, data storage, and internet access and trust in automated systems. The discussion also clarifies why the quantitative challenge occurs: customers may value speed but feel uneasy sharing their sensitive banking information if there is no clarity or when the system fails to comprehend their questions which are phrased in Shona or Ndebele or in a combination of both. This warrants the language inclusion, low data channels, privacy assurance, and visible human escalation. Eren (2021) concluded that trust is a key factor in satisfaction with banking chatbot usage. Similarly, the study by Ncube, Chinakidzwa and Mushayavanhu (2025) demonstrates that conversational intelligence has an impact on customers' satisfaction with customer service encounters in the banking sector in Zimbabwe.

Discussion 3: Improvement strategies and customer inclusion

During the focus group discussion, participants stated that:

FGP01: *“Banks should add local languages, improve escalation and educate customers.”*

FGP02: *“Banks should make chatbots more accurate and provide live-agent handover.”*

FGP05: *“Banks should update bots frequently using real customer complaints.”*

The focus group suggested local languages, quicker escalation, more accurate, customer education, privacy communication, more reliable services channels. The discussion presents the reason of why the improvement strategies achieved the highest construct mean in the quantitative result. NLP was not rejected by customers but pragmatic conditions were offered for making NLP more useful and inclusive were given. This is why it is advisable for banks to train chatbots with local queries, incorporate live agent handover, inform customers and improve security communication. The authors of Adamopoulou and Moussiades (2020) believe that continuous improvement of chatbots is possible by building more robust knowledge bases, whereas Graham et al. (2025) contend that the banking chatbots need to learn and grow in order to solve complex service issues.

4.12 Discussion of Findings

The study found that NLP technologies are being used by commercial banks in Harare CBD and that there was a greater degree of usage among existing customers who frequently use digital banking. Descriptively this was confirmed using the NLP utilization table and inferentially by the significant chi square result. Qualitative data also revealed that the primary uses of chatbots, automated response systems, and virtual assistants are for handling routine inquiries like checking balance, providing information on tariffs, card support, and branch information. The discovery aligns with that of Adamopoulou and Moussiades (2020), who say that chatbot technologies work best when customers are making a structured and repetitive request.

The study also indicated that NLP can improve customer experience primarily because of its ability to cut down the waiting time and make it more convenient and accessible outside the banks' hours. But it was also revealed that experience was poorer when a customer had needs for accuracy, personalization or handling complex complaints. The regression results revealed that customer experience had a significant influence on

customer satisfaction, which validated that customers are satisfied if they experience NLP during the service encounter. However, this is in line with Huang and Rust (2021) who suggest that the application of AI service should be based on service task type, and with Graham et al. (2025), which identify reliability and accuracy problems with chatbots as a limitation to their use.

The study additionally revealed that there are still implementation obstacles that are of concern. These ranged from generic responses, language restriction, internet/data costs, privacy issues, downtime of the system, lack of customer education, to challenging human-agent escalation. The results of the interviews and focus groups indicate that customers are frustrated when the bot gives a generic reply, or when they have to wait a long time to contact a human representative. This is consistent with the findings of Eren (2021) which revealed that satisfaction with chatbots is linked to trust and usefulness, and the Ncube, Chinakidzwa and Mushayavanhu (2025) study on the influence of conversational intelligence and task-technology fit on customer service encounter satisfaction in Zimbabwean banking.

Lastly, there was high support for improvement strategies. Customers and bank staff endorsed improved accuracy of response, Shona and Ndebele language facilities, faster transfer of customer to human agent, customer education, privacy assurance, collection of customer feedback and access to reliable 24 hour service. The focus group validated customer disaffirmation of NLP, but that it would be more inclusive, accurate and secure. This finding aligns with the arguments of Marak et al. (2025) that lower resistance barriers lead to higher adoption rates and Graham et al. (2025) who stressed the importance of ongoing learning and development in banking chatbots.

4.13 Chapter Summary

This chapter presented the findings of 199 questionnaire respondents, 13 interview participants and 5 focus group participants. The questionnaire response rate was 91.3%, the interview response rate was 86.7% and the focus group response rate was 100.0%. Overall, NLP technologies were found to enhance customer experience in commercial banks in Harare CBD, but their effectiveness depends on accuracy, language inclusion,

customer education, privacy assurance, system reliability and fast human-agent escalation.

CHAPTER V

SUMMARY OF FINDINGS, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This chapter presents the summary, objective-based conclusions and recommendations of the study on the effectiveness of Natural Language Processing (NLP) in enhancing customer experience in fintech, focusing on commercial banks in Harare Central Business District (CBD). The chapter is guided by the five research objectives presented in Chapter One and by the descriptive, inferential and qualitative findings presented in Chapter Four. The chapter first summarizes the study and major findings, then draws conclusions separately under each objective. It further provides objective-based recommendations, an implementation plan, contribution of the study, limitations, areas for further research and a final chapter summary.

5.2 Summary of Major Findings

The findings are summarized according to the study objectives so that the conclusions and recommendations remain directly linked to what the study set out to examine.

5.2.1 To examine the level of utilization of NLP technologies among commercial banks in Harare CBD

The findings showed that NLP utilization was moderate to positive. The overall mean for utilization was 3.50, indicating that respondents were aware of and were using NLP-enabled customer support, although the usage was not yet very strong. Awareness of NLP-enabled customer support recorded a mean of 3.60, access to chatbot or virtual assistant channels recorded 3.51, and usefulness for routine enquiries recorded 3.69. However, use of NLP support for quick banking assistance recorded a weaker mean of 3.20. This shows that NLP technologies are present in commercial banking, but customers use them more confidently for routine enquiries than for complex service problems.

Inferential analysis confirmed that utilization was linked to digital banking behaviour. The chi-square test showed a statistically significant association between frequency of

digital banking use and NLP use, with Pearson Chi-Square = 10.880 and $p < .001$. This means that customers who frequently used digital banking channels were more likely to use chatbots, virtual assistants and automated support systems. The finding is consistent with Marak et al. (2025), who found that performance expectancy and user-related adoption factors influence intention to use chatbots in banking services.

5.2.2 To evaluate the effectiveness of NLP technologies in enhancing customer experience

The study revealed that the NLP technologies are used to improve the customer experience primarily by convenience, speed and availability. Customers' perception of the overall customer experience was moderately positive (3.45). The mean scores for Convenience, reduced waiting time, access outside normal banking hours, and efficiency of the banking experience were 3.65, 3.61, 3.58, and 3.57, respectively. The findings indicate that the customers appreciated the NLP due to its convenience in saving time in visiting the banking halls and giving support services outside the bank service hours.

The results also revealed that accuracy and clarity/personalization were constraints for the effectiveness of NLP. The accuracy of responses was at 3.24, clarity of responses was at 3.38 and personalized service was at 3.16. Qualitative data revealed customer dissatisfaction when they receive a generic response from a chatbot or did not understand the context in which the query was made. Graham et al. (2025) also observed that customers appreciate banking chatbots for their speed and convenience, as well as their availability, but they do not like them if the accuracy of the answers and reliability of the bot is not high.

5.2.3 To determine the influence of NLP-based conversational systems on customer satisfaction

The results revealed that the NLP-based conversational systems positively affected customers' satisfaction, but it was still not in a good level. The mean of the overall customer satisfaction was 3.35. Customers were happy to recommend support with NLP and were pleased if there was a quick and helpful response from systems. But some respondents indicated that human involvement is still necessary for more intricate

matters, indicating that automated service isn't a complete substitute for human interaction in banking.

The inferential findings were strong evidence that customer satisfaction was influenced by NLP utilization and customer experience. The correlation between NLP utilization and customer satisfaction was $r = 0.798$ and correlation between customer experience and satisfaction was $r = 0.793$. The regression analysis also revealed that the utilization of NLP and customer experience were highly predictive of customer satisfaction ($p < 0.001$). This is consistent with the study conducted by Eren (2021), which revealed that customers' satisfaction with chatbots in banking is the result of their perception of the system as useful, reliable and user friendly.

5.2.4 To identify the challenges associated with implementing NLP technologies in banking

The primary issues identified for the implementation of NLP were limited customer education, poor human escalation, language limitations, privacy concerns, data cost and technical errors. The mean for implementation challenges was 3.37. The top challenge scores were for limited customer knowledge and difficulty accessing human agents. This implies that there were some customers who were not fully aware of the usage of the NLP banking service, and some customers who felt entrapped when the automated system could not address their issues.

The qualitative findings revealed that customers were worried about the aspects of trust and data privacy, and also whether the chatbot understood the local expressions or combination of languages. These are significant issues because banking is a place of sensitive financial information and customers require accurate, secure and accountable service of the bank. According to Chaves and Gerosa (2021), the interaction quality of chatterbots is related to the conversational design, social clarity and system responses to users' needs. The findings of Ncube et al. (2025) also show that in the banking sector in Zimbabwe, the link between conversational intelligence and customer service encounter satisfaction is mediated by the level of task-technology fit of the chatbot.

5.2.5 To propose strategies to improve the implementation of NLP technologies in financial institutions

The fifth objective was most successful in achieving positive outcomes. With a mean of 4.49, it is clear that the respondents strongly agreed that there are steps that can be taken to improve banking services using NLP. Strategies with the highest ratings were: Educating customers about the use of NLP systems, increasing response accuracy, enhancing communication of privacy and security, providing reliable systems around the clock, and making it easier to switch to a human agent.

The interviews and focus group results validated the fact that the participants didn't reject NLP technology. Rather, they wished to have a better bank. Participants highlighted the importance of Shona and Ndebele support, providing clear explanations on privacy, improving integration with the mobile, robust feedback systems and rapid escalation when the chatbot fails. Huang and Rust (2021) claim that the value of service lies in how artificial intelligence enhances customer interaction instead of replacing human service. Thus, NLP enhancement should be customer-focused, open and should be ongoing.

5.3 Conclusions

The study concludes that NLP technologies are being used by commercial banks in Harare CBD, but their utilization is still moderate and not fully mature. Customers are aware of chatbots, virtual assistants and automated response systems, and these tools are mainly used for simple and routine banking-related enquiries. However, use remains uneven because some customers still prefer human agents or branches when enquiries are sensitive, complex or unclear.

The study further concludes that NLP technologies enhance customer experience when the customer need is routine, time-sensitive and information-based. NLP reduces waiting time, improves access outside normal banking hours and increases convenience. However, its effectiveness is limited when customers require personalized advice, complex issue handling or accurate interpretation of detailed requests. Therefore, NLP

improves the functional side of customer experience more strongly than the relational and personalized side of banking service.

The findings also confirm that NLP-based conversational systems have a statistically significant positive influence on customer satisfaction. Customers are more satisfied when NLP systems are fast, accurate, understandable and useful. Satisfaction decreases when customers receive generic answers, experience repeated failed responses or struggle to reach a human agent. This means that NLP should be designed as a service-support tool, not as a barrier between customers and bank staff.

The study concludes that implementation challenges remain a serious constraint on the full effectiveness of NLP technologies in banking. The main barriers are limited customer education, weak escalation to human agents, language limitations, privacy and security concerns, data access costs and technical errors. These challenges reduce trust and weaken the customer experience even where NLP systems are available.

Overall, the study concludes that NLP can improve customer experience and customer satisfaction in commercial banking when it is accurate, secure, inclusive, reliable and supported by human assistance. The success of NLP in Harare CBD commercial banks therefore depends on moving from basic automated replies to intelligent, localized and continuously improved conversational support.

5.4 Recommendations

The recommendations that follow are organized by the research objectives to match the conclusions drawn from each of the objectives.

5.4.1 Improve utilization of NLP technologies

Commercial banks need to raise awareness among customers about the NLP support capability by conducting demonstrations on the branches, mobile banking notifications, SMS, WhatsApp prompts and/or staff-assisted onboarding. The chatbot and virtual assistant features should also be made more apparent in the mobile and internet banking apps of banks. Banks should incentivize low-frequency users to try out NLP

services by offering them simple services like checking balances, customer support via their card, and information about their branch.

5.4.2 Strengthen customer-experience outcomes

Banks need to provide more accurate, clear and personalized NLP responses. This can be done by training chatbot systems with frequent customer questions, customer complaints that were not resolved, actual call center cases, and common customer questions. Banks should also make the language of chatbots more streamlined and remove technical banking jargon where consumers require practical advice. This will make NLP systems able to go beyond convenience and speed and deliver more richer outcomes of customer experience.

5.4.3 Improve customer satisfaction

Commercial banks should consider each and every interaction with NLP as a part of customer satisfaction management. They should introduce post-chat satisfaction ratings, monitor chats which end up with no resolution and automatically flag the same for human follow-up. If a customer asks the same question again, or they are unhappy, the system should automatically provide a human response. This will avoid frustrating automated service.

5.4.4 Reduce implementation challenges

Banks need to tackle the key implementation hurdles by enhancing customer education, adding chatbot support in Shona and Ndebele, simplifying data-heavy chatbot designs, and communicating more effectively about privacy and offering clear pathways to access human agents. Information about how customer information is safeguarded in automated interactions should be disclosed in privacy notices. Furthermore, banks need to develop technical reliability, by keeping track of downtime, slow response times, and intent recognition failures.

5.4.5 Implement continuous improvement strategies

Banks need to put a continuous framework in place for NLP improvements. This structure should involve monthly review of chatbot logs, an evaluation of unanswered

questions, updating of knowledge bases, collecting customer feedback, and regular cross-checking of the accuracy of the chatbot. Banks, banking associations and regulators should also promote the responsible use of AI in banking, particularly regarding privacy, transparency, fairness, and customer redress.

5.5 Contribution of the Study

The study is original and adds to knowledge as it offers empirical evidence pertaining to the experience of NLP banking service in the context of commercial banking in Zimbabwe. The existing studies on banking chatbots have concentrated on general international scenarios, whereas this study concentrated on commercial banks in Harare CBD. It therefore provides contextual evidence of the customer's experience with NLP in the context of an emerging market banking environment.

The study also has methodological contribution by combining descriptive analysis, inferential analysis and thematic analysis. The descriptive findings revealed the extent of perceptions of the customers, the inferential findings revealed the statistically significant relationships between the key variables and the qualitative findings explain the reasons why participants perceived NLP systems positively or negatively. This was a combined approach which enhanced the interpretation of the findings.

The study offers practical recommendations to banks that can be implemented based on the recommendations given. These encompass raising customer cognizance, enhancing the accuracy of customer reactions, enhancing customer satisfaction monitoring, overcoming language and privacy obstacles, and developing continuous improvement processes. These recommendations can be used to guide commercial banks as they consider and create NLP services that are more customer centric and inclusive.

5.6 Areas for Further Research

Future studies need to focus on the application of NLP in customer experience in other provinces in Zimbabwe and compare customer experience between the banking customers in urban, peri-urban and rural areas. This would serve to determine if the

results of the Harare CBD relate to other areas where there are variations in internet connectivity, access to branches, and digital literacy.

There is a need to test the performance of local language NLP systems in the Zimbabwean banking environment in order to further investigate the system. However, as language barriers became a barrier, future research could consider the impact of using a Shona, Ndebele and mixed-language chatbot interface on customer understanding, trust and satisfaction.

Technical audits of banking chatbots should be done in the future as well. Real interaction logs could be utilized in such studies to measure actual response accuracy, intent recognition, escalation success, privacy compliance, downtime and response speed. This would be a complement to the customer-perception research with technical performance evidence.

Furthermore, longitudinal studies are suggested for assessing if customer satisfaction increases with the progression of banks' chatbot systems, the improvements in data security, and new training for customers along with enhanced human intervention. This would indicate the correlation of NLP maturity with continuous customer-experience improvement.

LIST OF REFERENCES

- Abis, D., Pia, P. and Limbu, Y. (2025) 'FinTech and consumers: A systematic review and integrative framework', *Management Decision*, 63(1), pp. 49-75. Available at: <https://doi.org/10.1108/MD-07-2023-1136>.
- Adam, A.M. (2020) 'Sample size determination in survey research', *Journal of Scientific Research and Reports*, 26(5), pp. 90-97. doi:10.9734/JSRR/2020/v26i530263.
- Adamopoulou, E. and Moussiades, L. (2020) 'An overview of chatbot technology', in Maglogiannis, I., Iliadis, L. and Pimenidis, E. (eds.) *Artificial Intelligence Applications and Innovations*. Cham: Springer, pp. 373-383.
- Adamopoulou, E. and Moussiades, L. (2020) 'Chatbots: History, technology, and applications', *Machine Learning with Applications*, 2, p. 100006. doi:10.1016/j.mlwa.2020.100006.
- Ahmed, S.K. (2025) 'Using thematic analysis in qualitative research', *Journal of Medicine, Surgery, and Public Health*, 6, p. 100198.
- Ashfaq, M., Yun, J., Yu, S. and Loureiro, S.M.C. (2020) 'I, Chatbot: Modeling the determinants of users' satisfaction and continuance intention of AI-powered service agents', *Telematics and Informatics*, 54, p. 101473. Available at: <https://doi.org/10.1016/j.tele.2020.101473>.
- Barroso, M. and Laborda, J. (2022) 'Digital transformation and the emergence of the FinTech sector: Systematic literature review', *Digital Business*, 2(2), p. 100028. doi:10.1016/j.digbus.2022.100028.
- Becker, L. and Jaakkola, E. (2020) 'Customer experience: Fundamental premises and implications for research', *Journal of the Academy of Marketing Science*, 48, pp. 630-648. doi:10.1007/s11747-019-00718-x.
- Braun, V. and Clarke, V. (2021) *Thematic Analysis: A Practical Guide*. London: SAGE.
- Chaves, A.P. and Gerosa, M.A. (2021) 'How should my chatbot interact? A survey on social characteristics in human-chatbot interaction design', *International Journal of Human-Computer Interaction*, 37(8), pp. 729-758.

- Cheng, Y. and Jiang, H. (2020) 'How do AI-driven chatbots impact user experience? Examining gratifications, perceived privacy risk, satisfaction, loyalty, and continued use', *Journal of Broadcasting & Electronic Media*, 64(4), pp. 592-614. Available at: <https://doi.org/10.1080/08838151.2020.1834296>.
- Cheteni, P., Matsongoni, H. and Umejesi, I. (2024) 'Artificial intelligence and its disruptive role in the South African fintech industry', *F1000Research*, 13, p. 1455. doi:10.12688/f1000research.155100.1.
- Chitimira, H. and Torerai, E. (2023) 'Policy implications and mobile money regulatory approaches to promote financial inclusion of the poor in Zimbabwe after the COVID-19 pandemic', *De Jure Law Journal*, 56, pp. 241-258. Available at: <https://doi.org/10.17159/2225-7160/2023/v56a17>.
- Consumer Financial Protection Bureau (2023) Chatbots in consumer finance. Available at: <https://www.consumerfinance.gov/data-research/research-reports/chatbots-in-consumer-finance/chatbots-in-consumer-finance/> (Accessed: 9 May 2026).
- Creswell, J.W. and Creswell, J.D. (2023) *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches*. 6th edn. Thousand Oaks: SAGE.
- Davis, F.D. (1989) 'Perceived usefulness, perceived ease of use, and user acceptance of information technology', *MIS Quarterly*, 13(3), pp. 319-340. Available at: <https://doi.org/10.2307/249008>.
- Dawadi, S., Shrestha, S. and Giri, R.A. (2021) 'Mixed-methods research: A discussion on its types, challenges, and criticisms', *Journal of Practical Studies in Education*, 2(2), pp. 25-36.
- Demirgüç-Kunt, A., Klapper, L., Singer, D. and Ansar, S. (2022) *The Global Findex Database 2021: Financial inclusion, digital payments, and resilience in the age of COVID-19*. Washington, DC: World Bank. Available at: <https://doi.org/10.1596/978-1-4648-1897-4>.

- Eren, B.A. (2021) 'Determinants of customer satisfaction in chatbot use: Evidence from a banking application in Turkey', *International Journal of Bank Marketing*, 39(2), pp. 294-311.
- Feyen, E., Frost, J., Gambacorta, L., Natarajan, H. and Saal, M. (2021) *Fintech and the digital transformation of financial services: Implications for market structure and public policy*. BIS Papers No. 117. Basel: Bank for International Settlements. Available at: <https://www.bis.org/publ/bppdf/bispap117.pdf> (Accessed: 9 May 2026).
- Field, A. (2024) *Discovering Statistics Using IBM SPSS Statistics*. 6th edn. London: SAGE.
- Gahler, M., Klein, J.F. and Paul, M. (2023) 'Customer experience: Conceptualization, measurement, and application in omnichannel environments', *Journal of Service Research*, 26(2), pp. 191-211. Available at: <https://doi.org/10.1177/10946705221126590>.
- Graham, G., Nisar, T.M., Prabhakar, G., Meriton, R. and Malik, S. (2025) 'Chatbots in customer service within banking and finance: Do chatbots herald the start of an AI revolution in the corporate world?', *Computers in Human Behavior*, 165, p. 108570. Available at: <https://doi.org/10.1016/j.chb.2025.108570>.
- Hair, J.F., Hult, G.T.M., Ringle, C.M. and Sarstedt, M. (2022) *A Primer on Partial Least Squares Structural Equation Modeling*. 3rd edn. Thousand Oaks: SAGE.
- Hornuf, L., Klus, M.F., Lohwasser, T.S. and Schwienbacher, A. (2025) 'Mobile fintech adoption in Sub-Saharan Africa: A systematic literature review and meta-analysis', *World Development*, 185, p. 106803.
- Huang, M.H. and Rust, R.T. (2021) 'A strategic framework for artificial intelligence in marketing', *Journal of the Academy of Marketing Science*, 49, pp. 30-50. Available at: <https://doi.org/10.1007/s11747-020-00749-9>.
- Huang, M.H. and Rust, R.T. (2021) 'Engaged to a robot? The role of AI in service', *Journal of Service Research*, 24(1), pp. 30-41.

- Jurafsky, D. and Martin, J.H. (2023) *Speech and Language Processing*. 3rd edn. Draft. Stanford: Stanford University.
- Jurafsky, D. and Martin, J.H. (2025) *Speech and language processing: An introduction to natural language processing, computational linguistics, and speech recognition with language models*. 3rd edn draft. Available at: <https://web.stanford.edu/~jurafsky/slp3/> (Accessed: 9 May 2026).
- Kamara, A.K. and Yu, B. (2024) 'The impact of FinTech adoption on traditional financial inclusion in Sub-Saharan Africa', *Risks*, 12(7), p. 115. Available at: <https://doi.org/10.3390/risks12070115>.
- Kaondera, P.R., Chikazhe, L., Munyimi, T.F. and Nyagadza, B. (2023) 'Buttressing customer relationship management through digital transformation: Perspectives from Zimbabwe's commercial banks', *Cogent Social Sciences*, 9(1), Article 2191432. doi:10.1080/23311886.2023.2191432.
- Kuria, J. (2024) *Fintech products and customer experience in the banking sector in Kenya: A case of Equity Bank fintech products*. MBA thesis. Africa Nazarene University. Available at: <http://repository.anu.ac.ke/handle/123456789/971> (Accessed: 9 May 2026).
- Kuyoro, M., Flötotto, M. and Gathinji, C. (2024) *Redefining success: A new playbook for African fintech leaders*. New York: McKinsey & Company.
- Makore, S.T.M. (2024) 'Regulating artificial intelligence to advance financial inclusion in South Africa', *Potchefstroom Electronic Law Journal*, 27(1). doi:10.17159/1727-3781/2024/V27I0A17488.
- Makudza, F., Jaravaza, D.C., Makandwa, G. and Mukucha, P. (2024) 'Disruptive artificial intelligence: Augmenting consumer experience through chatbot banking', in Singh, N., Kansra, P. and Gupta, S.L. (eds.) *Digital Influence on Consumer Habits: Marketing Challenges and Opportunities*. Bingley: Emerald Publishing, pp. 1-18. Available at: <https://doi.org/10.1108/978-1-80455-342-820241001>.
- Marak, Z.R., Pahari, S., Shekhar, R. and Tiwari, A. (2025) 'Factors affecting chatbots in banking services: The UTAUT2 and innovation resistance theory perspective',

- Journal of Innovation and Entrepreneurship, 14, Article 47. Available at: <https://doi.org/10.1186/s13731-025-00514-8>.
- Mashizha, M., Gondongwe, N. and Gumbo, L. (2025) 'Enhancing the adoption of digital banking in rural communities in Zimbabwe', *Acta Universitatis Danubius. Œconomica*, 21(2), pp. 114-133.
- Mtetwa, T. (2023) Digital banking strategy and financial performance of banks in Zimbabwe. MSc dissertation. University of Zimbabwe.
- Ncube, N., Chinakidzwa, M. and Mushayavanhu, T.P. (2025) 'Chatbot task-technology fit and conversational intelligence on customer service encounter satisfaction in the Zimbabwean banking sector', *Journal of Research and Innovation for Sustainable Society*, 7(1), pp. 41-66. Available at: <https://doi.org/10.33727/jriss.2025.1.5:41-66>.
- Nyagadza, B., Muposhi, A., Mazuruse, G., Makoni, T., Chuchu, T., Maziriri, E.T. and Chare, A. (2024) 'Prognosticating anthropomorphic chatbots' usage intention as an e-banking customer service gateway: Cogitations from Zimbabwe', *PSU Research Review*, 8(2), pp. 356-372. Available at: <https://doi.org/10.1108/PRR-10-2021-0057>.
- Parasuraman, A., Zeithaml, V.A. and Berry, L.L. (1988) 'SERVQUAL: A multiple-item scale for measuring consumer perceptions of service quality', *Journal of Retailing*, 64(1), pp. 12-40.
- Raithatha, R. and Storchi, G. (2024) *The State of the Industry Report on Mobile Money 2024*. London: GSMA.
- Reserve Bank of Zimbabwe (2026) Consolidated Banking Institutions' Information as at 31 December 2025. Harare: Reserve Bank of Zimbabwe.
- Russell, S.J. and Norvig, P. (2021) *Artificial Intelligence: A Modern Approach*. 4th edn. Harlow: Pearson.
- Saunders, M.N.K., Lewis, P. and Thornhill, A. (2023) *Research Methods for Business Students*. 9th edn. Harlow: Pearson.

- Shambira, L. (2020) 'Exploring the adoption of artificial intelligence in the Zimbabwe banking sector', *European Journal of Social Sciences Studies*, 5(6). doi:10.46827/ejsss.v5i6.942.
- Taherdoost, H. (2017) 'Determining sample size; how to calculate survey sample size', *International Journal of Economics and Management Systems*, 2, pp. 237-239.
- Taherdoost, H. (2021) 'Data collection methods and tools for research; a step-by-step guide to choose data collection technique for academic and business research projects', *International Journal of Academic Research in Management*, 10(1), pp. 10-38.
- Tshuma, S., Towo, T. and Dube, M. (2024) 'Consumer epiphanies on digital banking resilience in developing countries: Reflections from Zimbabwe', *Zimbabwe Journal of Business, Economics and Management*, 3(2), pp. 559-569.
- Yamane, T. (1967) *Statistics: An Introductory Analysis*. 2nd edn. New York: Harper and Row.

LIST OF APPENDICES

APENDIX 1. 1: Research instrument

THE EFFECTIVENESS OF NATURAL LANGUAGE PROCESSING (NLP) IN ENHANCING CUSTOMER EXPERIENCE IN FINTECH: A CASE STUDY OF COMMERCIAL BANKS IN HARARE CBD

Researcher	_____
Institution	_____
Program	_____
Supervisor	_____
Date	_____

1.0 Introduction to the Research Instrument

This research instrument is designed to collect primary data on the effectiveness of Natural Language Processing (NLP) in enhancing customer experience in FinTech, focusing on commercial banks operating in Harare Central Business District (CBD). The instrument is structured into three parts: a customer questionnaire, a bank staff interview guide and a focus group discussion guide. The questionnaire uses tick boxes and Likert-scale items to collect quantitative data, while the interview and focus group guides collect qualitative data on experiences, implementation challenges and improvement strategies.

1.1 Research Objectives Guiding the Instrument

- To examine the level of utilisation of NLP technologies among commercial banks in Harare CBD.
- To evaluate the effectiveness of NLP technologies in enhancing customer experience.
- To determine the influence of NLP-based conversational systems on customer satisfaction.
- To identify the challenges associated with implementing NLP technologies in banking.
- To propose strategies to improve the implementation of NLP technologies in financial institutions.

1.2 Instructions to Participants

- Participation is voluntary and respondents may withdraw at any time without penalty.
- Do not write your name on the questionnaire.
- Tick the box that best represents your view or experience.
- Where a written answer is required, provide brief and honest responses.
- All responses will be treated confidentially and used for academic purposes only.

2.0 Participant Consent Form

Please tick each box to confirm your consent before participating in the study.

- ☐ I confirm that the purpose of the study has been explained to me.
- ☐ I understand that my participation is voluntary.
- ☐ I understand that I may withdraw from the study at any time.
- ☐ I understand that my responses will be kept confidential.
- ☐ I agree that the information I provide may be used for academic research purposes.
- ☐ I agree to participate in this study.

Participant signature	_____
Date	_____
Researcher signature	_____

APENDIX 1. 2: Customer questionnaire

Section completed by bank customers who use or have access to digital banking services in Harare CBD.

Respondent Code	_____	Date	_____
Bank Branch/CBD Location	_____	Questionnaire Number	_____
Enumerator	_____	Time Started	_____

Section A: Demographic and Banking Profile

A1. Gender

- ☐ Male ☐ Female ☐ Prefer not to say

A2. Age group

- ☐ 18-25 years ☐ 26-35 years ☐ 36-45 years ☐ 46-55 years ☐ Above 55 years

A3. Highest level of education

☐ Ordinary/Advanced Level ☐ Certificate/Diploma ☐ Undergraduate degree ☐ Postgraduate qualification ☐ Other

A4. Employment status

☐ Employed ☐ Self-employed ☐ Student ☐ Unemployed ☐ Retired

A5. How long have you banked with your current commercial bank?

☐ Less than 1 year ☐ 1-3 years ☐ 4-6 years ☐ Above 6 years

A6. How often do you use digital banking services?

☐ Daily ☐ Weekly ☐ Monthly ☐ Rarely ☐ Never

A7. Have you ever used a chatbot, virtual assistant or automated response service from your bank?

☐ Yes ☐ No ☐ Not sure

A8. Main bank used in Harare CBD

☐ AFC Commercial Bank ☐ BancABC ☐ CBZ Bank ☐ Ecobank Zimbabwe
☐ FBC Bank ☐ First Capital Bank ☐ Metbank ☐ Nedbank Zimbabwe
☐ NMB Bank ☐ Stanbic Bank Zimbabwe ☐ TN CyberTech Bank formerly Steward Bank ☐ ZB Bank ☐ Other: _____

Section B: Level of Utilization of NLP Technologies

Please tick one option for each statement on how NLP-enabled banking services are used.

Statement	1 SD	2 D	3 N	4 A	5 SA
B1. My bank provides access to digital customer support such as a chatbot, virtual assistant or automated response system.	☐	☐	☐	☐	☐
B2. I am aware of the NLP-enabled digital support channels offered by my bank.	☐	☐	☐	☐	☐
B3. I use NLP-enabled customer support services when I need quick banking assistance.	☐	☐	☐	☐	☐

B4. NLP-enabled services are available through convenient channels such as mobile banking, website platforms or messaging platforms.	☐	☐	☐	☐	☐
B5. The bank encourages customers to use automated digital support before visiting a branch.	☐	☐	☐	☐	☐
B6. The NLP-enabled system is useful for routine enquiries such as balances, account issues, card queries and service information.	☐	☐	☐	☐	☐

Key: SD = Strongly Disagree; D = Disagree; N = Neutral; A = Agree; SA = Strongly Agree.

B7. Which NLP-enabled services have you used? Tick all that apply.

- ☐ Website chatbot ☐ Mobile banking app assistant ☐ WhatsApp or messaging bot
- ☐ Voice assistant/automated call service ☐ Automated email or SMS response ☐ I have not used any
- ☐ Other: _____

Section C: Effectiveness of NLP in Enhancing Customer Experience

Please tick one option for each statement on the effect of NLP services on your banking experience.

Statement	1 SD	2 D	3 N	4 A	5 SA
C1. NLP-enabled services reduce the time I spend waiting for banking assistance.	☐	☐	☐	☐	☐
C2. NLP-enabled services make banking more convenient.	☐	☐	☐	☐	☐
C3. NLP-enabled services improve access to banking support outside normal banking hours.	☐	☐	☐	☐	☐
C4. The responses provided by the NLP-enabled system are clear and easy to understand.	☐	☐	☐	☐	☐
C5. The NLP-enabled system provides accurate responses to my banking questions.	☐	☐	☐	☐	☐
C6. NLP-enabled services reduce the need to visit a physical branch.	☐	☐	☐	☐	☐

C7. NLP-enabled services make the overall banking experience more efficient.	☐	☐	☐	☐	☐
C8. NLP-enabled services improve personalised service delivery.	☐	☐	☐	☐	☐

Key: SD = Strongly Disagree; D = Disagree; N = Neutral; A = Agree; SA = Strongly Agree.

Section D: Influence of NLP-Based Conversational Systems on Customer Satisfaction

Please tick one option for each statement on satisfaction with conversational banking systems.

Statement	1 SD	2 D	3 N	4 A	5 SA
D1. I am satisfied with the speed of response from the NLP-enabled system.	☐	☐	☐	☐	☐
D2. I am satisfied with the quality of answers provided by the NLP-enabled system.	☐	☐	☐	☐	☐
D3. The system understands my banking queries without requiring many repeated explanations.	☐	☐	☐	☐	☐
D4. The system gives helpful guidance when my issue cannot be resolved automatically.	☐	☐	☐	☐	☐
D5. Using NLP-enabled services increases my trust in digital banking.	☐	☐	☐	☐	☐
D6. I would recommend NLP-enabled digital support to other bank customers.	☐	☐	☐	☐	☐
D7. I prefer using NLP-enabled systems for simple enquiries rather than queueing in a banking hall.	☐	☐	☐	☐	☐
D8. NLP-enabled systems make me feel that the bank is responsive to customer needs.	☐	☐	☐	☐	☐

Key: SD = Strongly Disagree; D = Disagree; N = Neutral; A = Agree; SA = Strongly Agree.

Section E: Challenges Associated with NLP Implementation in Banking

Please tick one option for each statement on challenges experienced when using NLP-enabled banking services.

Statement	1 SD	2 D	3 N	4 A	5 SA
-----------	---------	--------	--------	--------	---------

E1. The system sometimes fails to understand my questions.	☐	☐	☐	☐	☐
E2. The system gives generic answers that do not fully solve my problem.	☐	☐	☐	☐	☐
E3. Limited internet access or high data costs affect my use of NLP-enabled banking services.	☐	☐	☐	☐	☐
E4. Language limitations affect my ability to use NLP-enabled banking services effectively.	☐	☐	☐	☐	☐
E5. I am concerned about privacy and security when using automated digital support.	☐	☐	☐	☐	☐
E6. It is difficult to get assistance from a human agent after using the automated system.	☐	☐	☐	☐	☐
E7. Technical errors or system downtime reduce my confidence in NLP-enabled services.	☐	☐	☐	☐	☐
E8. Many customers are not sufficiently informed on how to use NLP-enabled banking services.	☐	☐	☐	☐	☐

Key: SD = Strongly Disagree; D = Disagree; N = Neutral; A = Agree; SA = Strongly Agree.

Section F: Strategies for Improving NLP Implementation in Financial Institutions

Please tick one option for each strategy that may improve NLP-enabled banking services.

Statement	1 SD	2 D	3 N	4 A	5 SA
F1. Banks should improve the accuracy of chatbot and virtual assistant responses.	☐	☐	☐	☐	☐
F2. Banks should provide NLP-enabled services in local languages such as Shona and Ndebele.	☐	☐	☐	☐	☐
F3. Banks should make it easier to move from automated support to a human agent.	☐	☐	☐	☐	☐
F4. Banks should educate customers on how to use NLP-enabled digital banking services.	☐	☐	☐	☐	☐

F5. Banks should strengthen data privacy and security protections on digital support platforms.	☐	☐	☐	☐	☐
F6. Banks should integrate NLP services with mobile banking and messaging platforms.	☐	☐	☐	☐	☐
F7. Banks should collect customer feedback after chatbot or virtual assistant interactions.	☐	☐	☐	☐	☐
F8. Banks should provide 24-hour digital support using reliable NLP-enabled systems.	☐	☐	☐	☐	☐

Key: SD = Strongly Disagree; D = Disagree; N = Neutral; A = Agree; SA = Strongly Agree.

Section G: Open-Ended Questions

G1. What do you like most about using chatbot, virtual assistant or automated customer support services in banking?

G2. What problems have you experienced when using NLP-enabled banking services?

G3. What should commercial banks in Harare CBD do to improve NLP-enabled customer support?

APENDIX 1. 3: Interview guide for bank staff and managers

Target participants: customer service officers, digital banking officers, IT officers, branch managers and operations managers in commercial banks operating in Harare CBD.

Interview Code	_____
Bank	_____
Participant Role	_____
Date	_____
Recording Permission	☐ Yes ☐ No

Objective 1: Utilisation of NLP Technologies

1. Which NLP-enabled tools are currently used by your bank for customer service?

Notes:

2. Which customer service functions are handled through chatbots, virtual assistants or automated response systems?

Notes:

3. How frequently do customers use these services compared with physical branch services or call centres?

Notes:

Objective 2: Effectiveness in Enhancing Customer Experience

4. How have NLP-enabled services affected customer waiting time, service speed and convenience?

Notes:

5. What evidence does the bank use to assess whether NLP improves customer experience?

Notes:

6. Can you provide examples of customer issues that are effectively handled through NLP-enabled systems?

Notes:

—

Objective 3: Influence on Customer Satisfaction

7. How do customers generally respond to chatbot or virtual assistant services?

Notes:

—

8. What feedback has the bank received on customer satisfaction with NLP-enabled services?

Notes:

—

9. In what ways do NLP systems affect customer trust, loyalty or willingness to use digital banking?

Notes:

—

Objective 4: Implementation Challenges

10. What technical, financial, organisational or regulatory challenges affect NLP implementation?

Notes:

—

11. How do language, customer literacy and data privacy issues affect NLP-enabled customer service?

Notes:

—

12. What challenges arise when automated systems fail to resolve customer queries?

Notes:

—

Objective 5: Improvement Strategies

13. What practical steps should banks take to improve NLP-enabled customer support?

Notes:

14. What training, infrastructure or policy support is needed to improve implementation?

Notes:

15. How can commercial banks make NLP systems more inclusive, accurate and trusted by customers?

Notes:

APENDIX 1. 4: Focus group discussion guide for customers

Target participants: selected customers of commercial banks in Harare CBD who have experience with digital banking or automated customer support services.

Focus Group Code	_____
Number of Participants	_____
Date	_____
Venue	_____
Recording Permission	☐ Yes ☐ No

Discussion Rules

- Participation is voluntary.
- Participants should respect each other's views.
- No personal names will be recorded in the final report.
- Participants may choose not to answer any question.

Discussion Questions

16. What digital banking services do you commonly use in Harare CBD?

Notes:

17. Have you used bank chatbots, virtual assistants or automated response systems?
Describe your experience.

Notes:

18. How do these systems affect service speed, convenience and access to banking support?

Notes:

19. Do these systems understand customer questions clearly? Give examples.

Notes:

20. How do chatbot or virtual assistant services affect your satisfaction with the bank?

Notes:

21. What challenges do customers face when using NLP-enabled banking services?

Notes:

22. How do language, privacy, internet access and trust affect your use of automated banking support?

Notes:

23. What should banks do to improve NLP-enabled services for customers in Harare CBD?

Notes:

APENDIX 1.5: Turnitin Report

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