Investigating the influence of chatbots on customer experience and frustrations in self-help functions in South Africa

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ABSTRACT

Organisations must provide responsive, efficient, and 24/7 customer service in the ever-evolving digital era. Chatbots have emerged as the preferred Artificial Intelligence (AI) technology, offering self-help functions to users in need of various digital services. This study addressed the scarcity of empirical studies on the use of chatbots as self-service agents in South African companies, particularly in exploring their contribution to customer experiences, both positive and negative. The study extended the Technology Acceptance Model (TAM) to investigate the antecedents of customer chatbot engagement and their subsequent impact on customer satisfaction and frustration within the context of self-help functions. Utilising a quantitative approach, data was collected through online survey questionnaires from a sample of 258 participants who had interacted with chatbots. Multiple linear regression analysis was employed for data analysis. Results revealed that perceived ease of use, performance expectancy, compatibility, and social influence positively influenced customer chatbot engagement. Additionally, customer engagement with chatbots had a significant positive correlation with satisfaction and a negative correlation with frustration. These results suggested that enhancing user-friendly interfaces, ensuring optimal performance, aligning with user preferences, and leveraging social influence could foster increased engagement. This study stressed the significance of understanding and optimising customer chatbot engagement for a positive user experience.

Keywords: *Chatbot engagement, customer experience, self-help tools, artificial intelligence, customer service, customer satisfaction, customer frustrations*

DECLARATION

I, _Lesego JM Raphela____________________________, declare that this research report is my work, except as indicated in the references and acknowledgements. It is submitted in partial fulfilment of the requirements for the degree of Master of Management in the field of Digital Business at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university.

Name: Lesego JM Raphela Signature:

Signed at ……Pretoria-East………………………………………………

On the ……20………………………. day of …………January…………… 2024….

DEDICATION

The dissertation is dedicated to my support system at home, my husband Andile who encouraged me from day 1 of post-grad. My sons Kwame(15, Kobi(11) and Banathi (22 Months) who at times endured a less supportive mom. It was worth it boys ☺. Kelebogile my sister, you stepped up in areas I didn't expect. Aunt D, Dr Dibuleng, and my tutor. Thank you so much for the guidance and your blunt honesty and feedback. Lastly, dad, look at your girl from up there, I hope you are proud.

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To Wits Business School, I am proud to be part of the Masters of Management in Digital Business alumni and it can only go up from here.

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LIST OF ACRONYMS

Acronym	Description
AI	Artificial Intelligence
AI-MC	AI-Mediated Communication
AI-CMC	Artificial Intelligence- Computer-Mediated Communication
CCE	Customer-Chatbot Engagement
CF	Customer Frustration
CO	Compatibility
CS	Customer Satisfaction
CX	Customer Experience
EE	Effort Expectancy
EFA	Exploratory Factor Analysis
FAQ	Frequently Asked Questions
FC	Facilitating Conditions
HCI	Human-Computer Interaction
IDT	Innovation Diffusion Theory
IT	Information Technology
KB	Knowledge Base
LSM	Living Standard Measure
NPL	Natural Language Processing
PAF	Principal Axis Factoring
PGC	Post-Graduate Committee
PE	Performance Expectancy
PEOU	Perceived Ease of Use
PU	Perceived Ease of Usefulness
Q&A	Questions and Answers
RPA	Robotics Processing Automation
SI	Social Influence
SME	Small and medium-sized businesses
SPSS	Statistical Package for Social Sciences

SST	Self-Service Technology
TAM	Technology Acceptance Model
TRA	Theory of Reasoned Action
UTAUT	Unified Theory of Acceptance and Use of Technology

CHAPTER 1

INTRODUCTION

1.1 Statement of purpose

This study delved into the experiences and challenges encountered by customers when utilising chatbots as self-help assistants, with a specific focus on companies operating in South Africa. The primary aim

was to assess the efficacy of integrating chatbots as self-help agents and to examine their role in facilitating customer self-service functions. Additionally, the study intended to offer insight into events or actions taken by the chatbot that could leave customers feeling frustrated. This could offer valuable information to organisations on what pitfalls to anticipate and how to mitigate those while optimising the benefits of using chatbots as self-help agents to enhance overall customer experience.

1.2 Background of the study

Navigating through today's ever-changing digital era, organisations have to adapt and offer more responsive, faster, and 24/7 customer service and support. Chatbots have become the artificial intelligence (AI) technology that most organisations use to fulfil customers' needs (Chen et al., 2021). Ramesh et al. (2004) defined Artificial Intelligence (AI) in the medical field as an extension of programs provided to the medical field by science and engineering to analyse complex medical data. These programs are utilised to formulate diagnoses and assist in the therapeutic decisions and predictions for the technicians to easily find a diagnosis in the medical field. Collins et al. (2021) stated in his study that "Artificial Intelligence" was coined and defined by John McCarthy as "the science and engineering of making intelligent machines".

Artificial Intelligence is "a 'system' not only a technology that can use data, learn by itself and act on its lessons to perform an assigned task(s) effectively and efficiently in any environment” (Gbadegeshin et al., 2021). This system must initially be trained (either by humans or another system). It can automate a process, direct itself and continuously learn from its activities. It can also act appropriately, independently, and intelligently with little human input (Gignac & Szodorai, 2024). It contains different forms of software and devices (Storey et al., 2024). Humans create it (Triguero et al., 2024). It is built on understanding existing phenomena and acts wisely based on its understanding (Sun et al., 2024). According to Ngai et al. (2021), chatbots are AI technologies utilising machine learning concepts to learn and improve their responses continuously.

Hill et al. (2015) refer to chatbots as tools expected to communicate and resolve customer queries and problems in human language. Although chatbots have faced challenges over the years, significant improvements have been experienced in the past decade. Ngai et al. (2021) conducted research comparing Knowledge Based (KB) chatbots with pure-play chatbots. They found that chatbots that used KBs built from Frequently Asked Questions (FAQs), historical Questions and Answers (Q&A), and consumer behaviour were more effective helping agents to customers.

Chatbots in eCommerce assist users in finding products, making personalised suggestions, simplifying order tracking, and responding to questions regarding shipping and refunds, and they can improve the shopping experience. According to (Seranmadevi & Kumar, 2019), Chatbots are also virtual assistants in eCommerce. They can aid users with various activities including appointment scheduling, creating reminders, managing to-do lists, and offering information on the weather, news, and other subjects.

As sales and lead generation aids, chatbots can interact with website users by initiating conversations regarding where they are in the browsing journey (Tran et al., 2021). Chatbots can assist the customer by making product recommendations and providing deals and discount guides during purchasing. Chung et al. (2020) examined how chatbot services affected customer happiness in luxury shopping. They showed that even while e-service agents do not always fully engage with the clients, digital service assistance tools can still help foster strong customer connections and influence customer purchase decisions.

Chatbots present interactive lessons, respond to student inquiries, provide tutoring support, and conduct assessments in education and training. Chatbots can support learning experiences by providing structures of academic literature. However, they are also open to misuse.

Consider tools such as ChatGPT, which may seem to contain all body of language, but when used verbatim by students, they lose their voice in academia. Kooli (2023) discusses the potential for abuse and exploitation of chatbots and AI systems in their article and the ethical issues surrounding their usage in research. His study concludes that human and AI research assistants require the primary researcher to monitor their performance and confirm their findings closely. The performance of the machines, however, might be far superior to that of a human. Additionally, machines might be more innovative and creative than humans (Kooli, 2023).

As self-help agents, chatbots are used to retrieve information. Chatbots can access databases or knowledge bases to retrieve and deliver information. They can help users locate certain information, such as corporate guidelines, product details, or FAQs (Caldarini et al., 2022).

The findings of this research could provide valuable insights to organisations seeking to implement or improve their chatbots as self-help tools and contribute to the growing body of literature on the use of AI-powered chatbots in customer service, customer experience and frustrations during these interactions. Customer satisfaction levels can be influenced by the quality of their engagement with chatbots (Yun & Park, 2022). According to Jiang et al. (2023), a well-designed chatbot can accurately understand customer queries, respond with pertinent and helpful information, and provide personalised assistance, leading to higher customer satisfaction levels. However, Huang and Dootson (2022) noted that customers may become frustrated when a chatbot cannot understand their queries or deliver pertinent and satisfying answers. Miscommunication and a drawn-out settlement process may emerge from a poorly built chatbot with restricted skills or a lack of contextual awareness. Therefore, once organisations understand the perceived impact of chatbots from the customer's perspective, they can make informed decisions on enhancing the customer experience, leading to higher customer satisfaction and retention.

This quantitative study aimed to explore how chatbots function as self-help agents for customers, intending to enable organisations to evaluate their customers' satisfaction and frustration levels. The study intends to give insight into preventative measures that organisations could take to avoid leaving customers frustrated by chatbots.

1.3 Research Problem

Despite AI's enormous benefits, some challenges may be associated with its use in human interactions (Abedin et al., 2022). While AI can enhance customer experiences, there is empirical evidence that customer-AI interactions (e.g., chatbots) are not smooth sailing. In the retail industry, chatbot implementation seems to be leading the pack; due to chatbots' ability to provide personalised recommendations and automated customer service support, consumer satisfaction levels have grown (Ruan & Mezei, 2022). Aslam (2023) quotes (Razmak & Bélanger, 2018), who states that according to academics, the efficiency of technology use should be assessed using factors such as perceived usefulness and perceived ease of use. The jury is still out on how chatbots influence customer satisfaction and frustrations in self-help service situations.

Unlike earlier studies that mainly examined factors affecting adoption of chatbots (Josh, 2021; Alt et al., 2021; Mostafa and Kasamani, 2022), this study advanced the understanding of customer-chatbot interactions by extending the UTAUT to explore engagement's impact on satisfaction and frustration. The extension of UTAUT was necessary as this study moved beyond merely identifying the actual use antecedents to unravel the dynamics of how engagement shapes user experiences. In addition, studies mainly focused on the positive outcomes, particularly user satisfaction, neglecting the equally important dimension of customer frustration (Crolic et al. 2022; Li & Wang, 2023). This study introduced a new approach by explicitly measuring customer frustration, a facet often overlooked in previous research.

This study investigated the influence of chatbots on customer experience and frustrations in self-help functions within companies in South Africa. There is also a dearth of empirical research on the use of chatbots as self-service agents in especially within the South African telecommunications sector, and whether their use contributes to a positive or negative customer experience.

The study intended to explore the antecedents of customer chatbot engagement, the impact on customers' satisfaction levels, and the potential issues that may arise from using chatbots, such as misunderstandings, miscommunications, and overall inability to comprehend the customer’s request or query. By closely examining these factors, the study aimed to provide insights into how organisations can optimise their chatbots to improve customer experiences and minimise potential frustrations. This study sought to provide empirical knowledge that could contribute towards closing the research gaps in the use of chatbots as self-help and self-service functions in South African Industries.

1.4 Research Questions

i. What are the antecedents to customer-chatbot engagement?

ii. What is the impact of customer-chatbot engagement on customer satisfaction?

iii. What is the impact of customer-chatbot engagement on customer frustrations?

1.5 Rationale

Chatbots have demonstrated their effectiveness as shopping assistants for online market places like TMall. However, literature suggests that they may not excel as query or problem-solving agents, often lacking the ability to understand customer frustration. This is where human agents shine, as they are better equipped to address and resolve customer issues (Ruan & Mezei, 2022).

This study aimed to contribute to the growing body of literature regarding chatbots and how customers perceive them when utilised as self-help tools for customer service. The outcomes could help organisations implement chatbots as self-help mechanisms to gain insights into how other customers in South Africa have experienced chatbots and optimise the effectiveness of their usage to contribute to the positive realisation of organisational strategy.

The study contributes to the knowledge of the Technology Acceptance Model (TAM) theory by directly highlighting the usefulness of chatbots as self-help tools in the telecommunications industry in South Africa. The current body of knowledge has very little to no research paper that addresses this topic specifically in South Africa. Lubbe and Ngoma (2021) have contributed to the body of knowledge by testing this theory as part of an emerging market and conducted their surveys only in Gauteng province.

Lastly, this study could also give insight to organisations who have already implemented chatbots as self-help tools on how their customers perceive them, how they can better improve, and the ability to identify which areas are best suited for chatbots and human agents.

1.6 Delimitations of the study

- The study is based on customers or web users interacting with a chatbot.

- The study is based on customers interacting with one of the chatbots in South African companies who have made this function available on their platforms.

1.7 Definition of terms

Table 1: Definition of terms

Terminology	**Definition**
Chatbot	A computer program designed to simulate conversations with human users, especially over the internet.
Self-service	Self-service tools are applications, platforms, or systems that allow users to perform various tasks or obtain information without needing direct assistance from customer support or service personnel.
Artificial Intelligence	Artificial intelligence (AI) is a branch of computer science that deals with developing computer programmes to perform tasks that would otherwise require human intelligence (Chen et al., 2020).
Customer experience	Customer experience is what the customer feels over time while interacting with an organisation's products and services through various channels.
Self-service Technologies	Self-service technologies (SSTs) are technological interfaces and systems that enable individuals to perform tasks and access services independently without direct assistance from service providers. These technologies enhance user autonomy and efficiency by allowing users to interact with automated systems for various service-related activities (Meuter et al., 2005).

1.8 Assumptions

- The study assumed that all respondents had access to the internet and a device to answer the provided questions.
- The study assumed that all respondents have interacted with a Chatbot before as a self-help mechanism.
- The study assumed that companies forming part of this research were keen to learn from it to improve customer interactions and experience.
- The study assumed that respondents were customers of a telecommunications company in South Africa and had interacted with that specific chatbot.

1.9 Chapter Outline

Chapter 1 aims to summarise the research to be undertaken by discussing the literature underpinning chatbots in digital self-service platforms. Research questions are formulated to be investigated as subject matter drivers.

Chapter 2 outlines the literature review conducted. Containing the literature review is the theoretical framework covered by other research in the field. The aim is to give context to research methodologies and empirical reviews covered by scholars. To investigate the factors that influence Chatbot engagement and customer experience, the technology acceptance model (TAM) model is used to analyse customer experience, followed by the research method and proposed hypotheses.

Chapter 3 describes the data collection methods and research tools used to meet the study's objectives.

Chapter 4 presents the findings from investigating the variables influencing customer engagement outcomes while utilising chatbots for self-help/self-service functions in South Africa.

Chapter 5 discusses in detail the outcomes of the data analysis reported in Chapter 4, including the results relevant to testing hypotheses and the demographic characteristics of the respondents.

Chapter 6 outlines the conclusions of the influence of chatbots on customer satisfaction and frustrations study. Furthermore, it makes recommendations to South African organisations and suggests areas for future research.

CHAPTER 2

LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1 Introduction

The use of chatbots in various sectors has increased in recent years due to technological advancement, pressure on companies to do more with less money, changing demands of customers, the need for efficiency, and handling huge volumes of orders and queries from customers or users. This is noticed by the uptake of chatbots heightened in various sectors such as education, telecom, e-commerce, etc. The COVID-19 pandemic fuelled the increase in the use of chatbots. This chapter reviews the literature on similar studies conducted on chatbots implemented as self-help or self-service functions in organisations. Furthermore, the chapter discusses the theoretical framework used as a foundation to develop the hypothesis presented later on in the chapter. The impact of chatbots on customer satisfaction and frustrations is explored in this literature review, which looks at several important constructs such as Customer-Chatbot Engagement (CCE), Perceived Ease of Use (PEOU), Performance Expectancy (PE), Compatibility (CO), Social Influence (SI), and Customer Satisfaction (CS). Lastly, the chapter delves into its historical background before concluding by deriving a list of hypotheses to address. The literature review includes studies conducted in South Africa and internationally, as well as those that focused on other industries on the use of chatbots.

2.2 Theoretical Framework: Unified Theory of Acceptance and Use of Technology (UTAUT) model

The Unified Theory of Acceptance and Use of Technology (UTAUT) is a prominent theoretical framework that explains and predicts individuals' acceptance and use of technology. Developed by Venkatesh et al. (2003), the UTAUT consolidates various models and theories, including the Technology

Acceptance Model (TAM), the Theory of Reasoned Action (TRA), and the Innovation Diffusion Theory (IDT) (Davis, 1989; Ajzen, 2020). This integration allows UTAUT to encompass various factors influencing technology adoption and use.

UTAUT posits four core determinants that impact users' acceptance and use of technology: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) (Hutabarat et al., 2021). Performance Expectancy refers to users' perceptions of how much technology will enhance their performance (Venkatesh et al., 2003). Effort Expectancy relates to the perceived ease of use, while Social Influence considers the impact of societal factors and subjective norms. Facilitating Conditions involve the perceived support and resources available for technology use (Venkatesh et al., 2003).

Furthermore, UTAUT introduces three moderators: gender, age, and experience (Venkatesh et al., 2003). These moderating factors influence how the core determinants affect behavioural intentions and use behaviour. For example, the impact of social influence may vary across different demographic groups.

The UTAUT is relevant in customer chatbot engagement as the theory forms the basis of understanding the antecedents of user acceptance and use of the technology. Users' expectations regarding the chatbot's performance (performance expectancy) and the perceived effort required for interaction (effort expectancy) are pivotal factors. Social Influence becomes critical when considering the influence of peers or social norms on adopting chatbot technology. Additionally, the availability of facilitating conditions, such as easy access to the chatbot and adequate support, plays a crucial role in determining engagement (Gümüş & Çark, 2021).

Moreover, the UTAUT's relevance extends to understanding the subsequent impact of chatbot engagement on customer satisfaction and frustration. This is consistent with the predictions of the Expectancy Disconfirmation Theory (EDT).

Expectancy Disconfirmation Theory holds that consumers form judgments about products or services using their prior expectations about the characteristics or benefits offered by the given product or service (Van Ryzin, 2006). Integrating the UTAUT and EDT helps in understanding how users' interactions with chatbots influence their overall satisfaction or frustration. If users perceive the chatbot as effective and easy to use, it will likely positively influence their overall satisfaction (El Bakkouri et al., 2022). Conversely, if the chatbot fails to meet performance expectations or presents usability challenges, users may experience frustration (Gümüş & Çark, 2021). The initial expectations formed through UTAUT's constructs are evaluated against the actual satisfaction or frustration with chatbot use. When these expectations are confirmed or exceeded, users experience positive disconfirmation, enhancing satisfaction (Elkhani & Bakri, 2012). However, when expectations are unmet, negative disconfirmation occurs, leading to dissatisfaction and frustration.

Therefore, the combination of UTAUT and EDT provides a comprehensive framework for investigating the antecedents of customer chatbot engagement and its subsequent impact on satisfaction and frustration. Considering factors such as performance and effort expectations, social influence, and combability, the study can gain insights into technology acceptance and use dynamics. The UTAUT serves as a foundation for understanding the nuanced relationships within customer chatbot engagement, offering a structured and holistic approach to guide empirical investigations and inform practical implications in the field.

2.3 Empirical Review

Self-Service Technologies (SSTs) are computer-based systems that allow customers to complete transactions or obtain information without the assistance of a human service representative (Wang et al., 2013). Several successful automation initiatives, such as chatbots for customer service, have been made over the recent years. Chatbots help businesses cut expenses and save time and effort while improving the customer experience (Joshi, 2021). Chatbots that facilitate self-service without any human intervention are regarded as Self-

Service Technology (SST); the chatbots might be efficient in assisting customers to perform self-service functions; however, they fall short at times to understand customer inputs or typed queries (Sheehan et al., 2020).

Lubbe and Ngoma (2021) utilised a TAM to investigate the acceptance of chatbots for self-service technologies. Their study was conducted when emerging markets also found themselves impacted by the COVID-19 pandemic, having to pivot their efforts and respond by implementing solutions such as chatbots to remain in business. Their empirical study found that the number of females who participated outweighed the number of males, and most respondents were between 18 and 35. This is not surprising as the study was initially targeted at millennials. However, they do not state the number of millennials in the higher ages. They also found that most respondents held a higher education qualification, such as diploma or degree, with English as their home language. This leaves assumptions about race which were not considered in this study. The study ousted any information from customers who indicated that they had never interacted with a chatbot. The authors could have introduced an elimination question that could first be stated to avoid collecting unnecessary data.

This literature introduces task-orientated chatbots. Liu et al. (2023) conducted a comparative study based in Hong Kong to investigate the adoption of task-orientated chatbots. The aims were to determine the antecedents of satisfaction and usage intentions that differ based on different chatbot adoption and development stages. The study compared the adoption of the chatbots in Hong Kong and mainland China. The key findings were that users in Hong Kong believe that the main advantage of utilising task-oriented chatbots is that they can obtain comprehensive and pertinent information. Secondly, they found that the characteristics and state of development of chatbot apps mean that system quality may not necessarily have beneficial effects on user satisfaction, as they have progressive chatbot applications, and adoption in mainland China seems to be better than in Hong Kong as a result of exposure to a variety of chatbots.

Hohenstein and Jung (2020) explained AI-Computer Mediated Communication (AI-CMC) and its use across all social media platforms and popular applications and devices. When AI-CMC is viewed as an enhancer of a user’s daily tasks, it is seen as trustworthy and reliable, as there is no sense of personal engagement. Users do not tend to think that the text predictor is driven by an AI programme that learns word patterns and can offer a subsequent word based on usage or grammar.

Until recently, businesses were forced to use human agents to handle complex customer service tasks due to chatbots' functional constraints, with chatbots being used primarily in supporting capacities. The development of generative AI apps like Bard and ChatGPT looks to make complete automation of customer support interactions possible eventually (Huang et al., 2024).

2.3.1 Chatbot Customer Experience

2.3.1.1 Implemented in industries across industries

According to BusinessTechSA (2018), 46 percent of companies in South Africa are implementing or piloting AI in different forms. It could be chatbots, Robotics Processing Automation (RPA), and other analytics to improve customer service. Although this technology introduces innovative ways of doing business, in a country like South Africa, where the employment rate is sky-high, this poses a social economic issue.

In the **health** industry, Suharwardy et al. (2023) conducted a randomised trial on pregnant women from the age of 18 and above to test if chatbots will display a positive effect on moods during pregnancy (Perinatal) and after giving birth (postnatal). The authors realised that most women need a friend to chat with confidentially during these times, and a chatbot became the companion of choice for this study compared to women who received usual care from human caregivers. The outcomes were that a higher percentage of women with chatbot companions showed healthier mental states than those with human caregivers.

Students and staff at institutions could benefit from the speedy and individualised services that chatbot technology offers. Teachers can use various technological tools, like chatbot systems, to administer instruction through an online or a classroom platform (Okonkwo & Ade-Ibijola, 2021).

Chatbots can instantly provide students with standardised details, such as course contents, practice questions, and answers. Even though there are numerous ways of engagement between educators and students, chatbot technology can provide students with a more personalised and engaging learning environment (Pérez et al., 2020).

Artificial intelligence (AI) tools such as ChatGPT and GPT-3 have gained much attention lately because of their remarkable advancements, demonstrating their ability to produce believable output that is hard to tell apart from human text (Lin & Chang, 2023). This has raised questions concerning their usage by students in contexts of higher education and resulted in their banning at certain schools. Academic integration of these AI technologies is problematic since it is hard to distinguish between the written work students submit for evaluation and that generated by the AI tools. The main concern is that research papers produced by AI technologies might potentially undermine the authority and credibility of human academics (Howell & Potgieter, 2023).

In the **retail** industry, in a study done in Saudi Arabia, Alboqami (2023) investigated the variables influencing customer intentions to use chatbots in the retail sector. The study highlighted that chatbots instantly respond to a customer's inquiry and suggest related products based on the customer's selection by utilising predictive modelling and Machine Learning (ML) algorithms. Further, the study highlighted one advantage of chatbots in retail services: customers can stay in touch with the chatbot to check on the status of their orders and get after-sale assistance. Chatbots can, therefore, be very beneficial for small and medium-sized businesses (SMEs).

Fashion chatbot technology has entered the retail space with stores such as the famous Tmall, an online shopping centre from China where a chatbot provides a full-on shopping experience. Chatbots suggest fashion material, save browsing time by zoning in on historical likes, and retain customer preferences, increasing customer happiness and loyalty. Several well-known companies that employ chatbot technology in this way include Victoria's Secret, Tommy Hilfiger, Burberry, Sephora, and Estée Lauder (Aslam, 2023).

In the past, chatbot marketing apps effectively assisted consumers with website navigation and online transactions. Modern chatbots are distinguished by conversational interfaces that enable them to resemble human conversations, allowing them to function as virtual assistants and as virtual buddies. To the extent that clients may not even realise they are engaging with a chatbot and not a natural person. Additionally, chatbots have developed into more interactive and valuable tools that may be used for reading product reviews, finding and researching products, comparing products, accessing coupons that have been saved, placing orders, keeping track of orders, and receiving incentives and loyalty points (Alboqami, 2023).

In the **banking** industry, chatbots are primarily employed to enhance the quality of customer assistance and service by automatically and instantly responding to consumer inquiries. Businesses think that not hiring customer service agents can result in significant cost savings (Hsu & Lin, 2023).

The banking sector has discovered that deploying chatbots is advantageous since they can assist their clients in completing various activities like processing transactions, handling account queries, and providing quick answers to frequently asked questions. According to Hazar et al. (2023), chatbot use in banking worldwide is making good strides; however, Arabic countries are lagging in adopting this technology, primarily because of the complexity of the Arabic language.

These are some of the few industries we discuss in this paper, and there are many more chatbot applications in other industries.

2.4 Conceptual Framework

This study adopts the UTAUT as its conceptual framework to examine the antecedents of customer chatbot engagement. The EDT is also utilised to investigate the subsequent impact of customer chatbot engagement on satisfaction and frustration. UTAUT integrates critical determinants such as performance expectancy, effort expectancy, social influence, and facilitating conditions, providing a comprehensive understanding of individuals' acceptance and use of technology (Venkatesh et al., 2012). This study aimed to uncover the nuanced relationships between users' expectations, social influences, combability (Mostafa & Kasamani, 2022), and their overall satisfaction and frustration with chatbot engagement. Several studies have adopted the UTAUT to investigate chatbot adoption, extending the theory to suit different contexts (Mostafa & Kasamani, 2022; Paraskevi & Vaggelis , 2022).

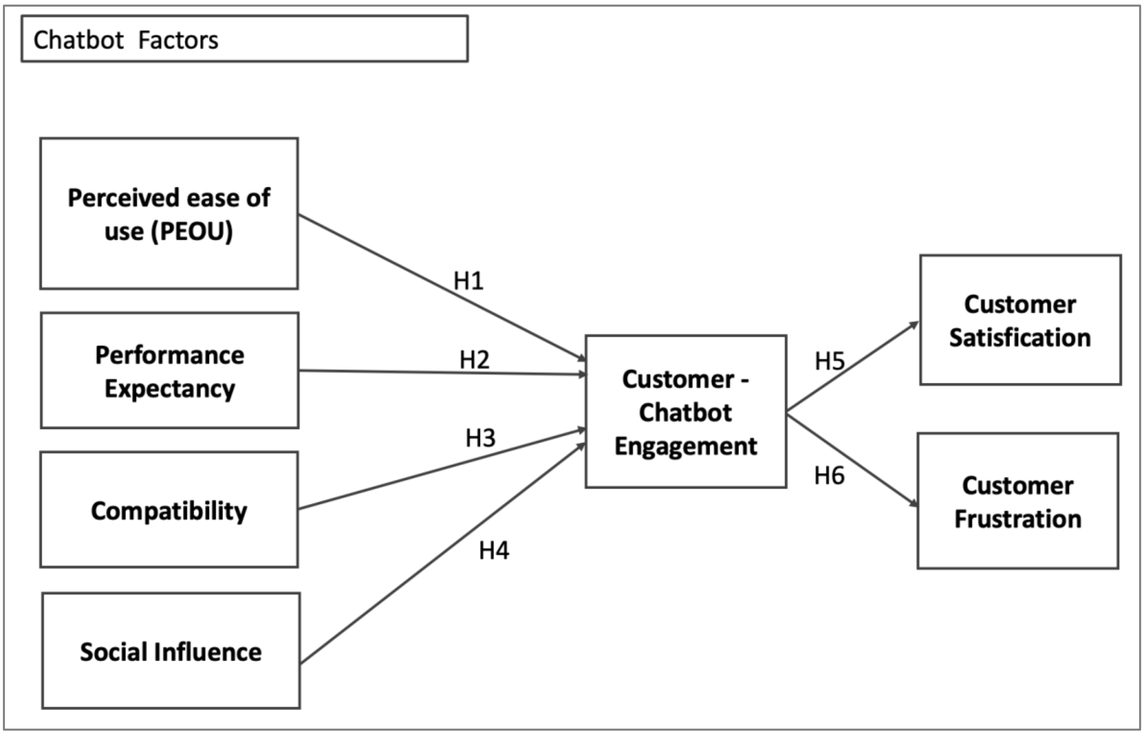

Figure 1: Conceptual Model

Figure 1~~Figure 1~~ shows that the study investigated the antecedents of customer-chatbot engagement: PEOU, PE, CO, and SI. Customer chatbot engagement/use will influence overall customer satisfaction (CS) and frustration (CF).

Each of the hypothesised relationships is further argued below.

2.4.1 Perceived ease of use (PEOU) and customer-chatbot engagement

Perceived ease of use refers to a user's perception of how easy it is to utilize a new technology such as a chatbot. It establishes the likelihood of people's perception of how simple it is to use new technology (Davis, 1989). When users see a chatbot as essential and valuable, it directly improves their whole chatbot experience. The perception of ease of use is formed when customers find the chatbot interface intuitive, user-friendly, and straightforward to navigate.

A chatbot's perceived ease of use is increased when it is created with clear instructions, well-organized menus, and simple prompts. Customers are more likely to engage actively and extensively with the chatbot when they are at ease and confidently navigating and utilising it. As it directly affects customer engagement, contentment, and the chance of using the chatbot as a helpful resource in future encounters, businesses should prioritise their chatbots' design and user experience to ensure they are seen as simple to use (Saadé & Kira, 2007). The positive relationship between perceived ease of use and customer-chatbot engagement leads to this hypothesis:

***Hypothesis 1 (H1) Perceived ease of use positively influences customer chatbot engagement*.**

2.4.2 Performance expectancy (PE) and customer-chatbot engagement

Customers are more likely to feel satisfied and confident in a chatbot's abilities when they have high expectations for the chatbot's performance and believe that it lives up to or exceeds those expectations (Eren, 2021). Performance expectancy is one of the four constructs of the UTAUT model (Venkatesh et al., 2003).

Loureiro et al. (2018) investigated technology acceptance in the context of retail websites. The study found that customers are likelier to trust the chatbot and actively interact in an atmosphere with a favourable sense of expected performance. They are more likely to engage in meaningful conversation, ask in-depth and pertinent questions, give accurate answers, and devote time and effort to the exchange (Cheng et al., 2021).

Joshi (2021) found performance expectancy to be the most important factor explaining behavioural intention and overall customer experience in investigating the adoption of customer service chatbots among Millennials in India. Therefore, performance expectancy is expected to impact customer-chatbot engagement positively. The following hypothesis was formulated:

Hypothesis 2 (H2): Performance expectancy positively influences chatbot engagement.

2.4.3 Compatibility (CO) and customer-chatbot engagement

Araújo and Casais (2020) conducted a study that used the TAM to examine the use of chatbots as e-commerce shopping assistants. The study revealed that compatibility and attitude towards mobile advertising significantly impacted their acceptance of chatbots. Furthermore, compatibility was the most significant predictor of attitude variance among users.

Alt et al. (2021) identified the factors that impact customers' inclination to embrace chatbot technology in the banking industry, extending the technological acceptance model to include compatibility, consumers' perceived privacy risk, and service awareness. Notably, this study found that perceived usefulness and compatibility were the two key variables that had the greatest impact on consumers' intention to use chatbots. The results highlighted that customers were more likely to embrace the technology when they believed banking chatbots would fit into their daily routine. Furthermore, Mostafa and Kasamani (2022) showed that compatibility, perceived ease of use, and social impact vastly increased consumers' initial trust in chatbots.

In a study by Hari et al. (2021) on the antecedents and consequences of customer brand engagement using banking chatbots, compatibility was found to have a favourable impact on customer brand engagement via chatbots, which in turn influenced customer satisfaction and desire to use the company in the future.

Therefore, it can be deduced that the perceived compatibility of a chatbot has a positive influence on chatbot engagement. Customers are more likely to engage with a chatbot effectively when they believe it is compatible with their expectations and needs. The following hypothesis was therefore specified:

Hypothesis 3 (H3): Perceived compatibility positively influences chatbot engagement.

2.4.4 Social influence (SI) and customer-chatbot engagement

Konya-Baumbach et al. (2023) argued that customers are more likely to display higher levels of engagement with chatbots when they believe that their interactions with a chatbot are being viewed or assessed by others, such as peers or customer care agents. Joshi (2021) also found that social influence significantly predicted chatbot adoption. Alt et al. (2021) presented a study on banking, finding that social influence directly and dramatically impacts customer engagement with chatbots. Alt et al. (2021) explained that people are more likely to embrace technology if they believe the banking chatbot would align with their lifestyle and social influence.

Gopinath and Kasilingam (2023) also found that perceived social influences directly impact chatbot use, arguing that humans are social beings whose behaviours are often influenced by their perception of what others think or do, especially family and friends. The use of social media is another influential component. Customers may be encouraged to interact with a chatbot positively when they perceive that their peers or other influential people are favourably interacting with it (Adam et al., 2020). Based on the review of studies, a positive relationship between social influence and customer chatbot engagement can be inferred. The following hypothesis was specified:

Hypothesis 4 (H4): Perceived social influence positively influences customer chatbot engagement.

2.4.5 Customer-Chatbot Engagement and Customer Satisfaction

Customers' satisfaction is measured by the goods they purchase or services they receive (George & Kumar, 2014). Customer satisfaction can also be viewed as an arbitrary assessment of happiness or disappointment. Customers frequently assess a product's performance compared to their expectations (Camilleri & Filieri, 2023). Chatbots are now an essential customer support component in the digital age, acting as many firms' initial point of contact. Customer satisfaction levels are substantially impacted by the quality of their engagement with chatbots (Yun & Park, 2022). According to Jiang et al. (2023), a well-designed and intelligent chatbot can accurately comprehend consumer questions, respond with pertinent and helpful information, and provide personalised assistance, leading to higher customer satisfaction levels.

Xie et al. (2024) examined the efficacy of chatbots that employed clever and comical language to provide online customer support. The results of a few experimental investigations confirmed that the humorous banter of chatbots dramatically improves customer satisfaction. Zhu et al. (2023) found that well-designed chatbots foster positive engagement, improving user satisfaction. Hsu and Lin (2023) also found that chatbot service quality significantly improves customer satisfaction. This was found in the results of their qualitative study, as customers indicated that more humanised chatbot responses and very high service recovery qualities aided the high level of customer satisfaction. Therefore, based on the discussion, the following hypothesis was specified:

Hypothesis 5 (H5): Customer-chatbot engagement positively influences overall customer satisfaction.

2.4.6 Customer-chatbot engagement and customer frustration

Customer frustration is when users react negatively to challenges, obstructions, or unsatisfying encounters with the chatbot. Frustrations include things like mistakes, misunderstandings, or chatbot functionality restrictions. Huang and Dootson (2022) studied frustrations caused by chatbots to customers. They further investigated how disclosing early to a customer that he/she is interacting with the chatbot is much more beneficial than disclosing later. Customers may become frustrated when a chatbot cannot comprehend their questions or deliver pertinent and satisfying answers. Miscommunication and a drawn-out settlement process may emerge from a poorly built chatbot with restricted skills or a lack of contextual awareness.

Customers tend to develop a negative impression if they find out that there is an opportunity to engage with a human instead of a chatbot, leading to customer frustration. Park et al. (2021) conducted a study investigating factors that push customers to use profanity when engaging with chatbots. As much as every company aims to develop a chatbot that communicates as close to human life as possible, it also has downsides. For example, a chatbot that communicates very well but continues to be stuck in a loop and unable to resolve an issue. This inability of a chatbot to resolve the issue and being stuck in a loop are contributing factors to customer frustrations. A study by Van Der Goot and Pilgrim (2019) on using chatbots for customer service and queries revealed that customers shared a singular view when they failed to understand and answer their queries, leading to customer frustration.

Crolic et al. (2022) assumed that users interact with a self-service chatbot from an angry or irritable state, finding that user anger or frustration can also develop during the interaction with the chatbot. Tamara et al. (2023) conducted a qualitative study investigating how Gen Z perceives chatbots and how they impact customer engagement and the e-commerce experience. They concluded that the chatbots' quick or instantaneous response capabilities and personalised advice can enhance customer satisfaction and reduce frustration.

It can be inferred that a poorly designed chatbot with few features and inadequate responses might cause annoyance, frustration, and even a terrible impression of the company. Customers may become frustrated and dissatisfied when chatbots are unable to comprehend and respond to intricate or unusual customer inquiries (Li & Wang, 2023). Chatbots could stray from the pre-written script, misinterpreting the inquiries of the clients and providing inaccurate information (Gümüş & Çark, 2021). Hence, the following hypothesis was specified:

Hypothesis 6 (H6): Customer chatbot engagement reduces customer frustration.

2.5 Conclusion of Literature Review

The reviewed literature addressed the research objectives to understand factors that influence chatbot adoption by South Africans and how engagement with the chatbot can positively influence customer experience (which leads to customer satisfaction) or negatively (which leads to customer frustration). Although studies on chatbot adoption as a self-help/self-service function in emerging markets such as South Africa are limited, literature on chatbot adoption as a self-help/self-service function exists in the international space. This study was based on the UTAUT model as its conceptual framework, and it investigated the factors that drive customer-chatbot engagement and, in turn, consumer satisfaction and frustration levels. A conceptual framework for empirical research was formulated, specifying six (6) hypotheses empirically tested in this study. The following chapter presents the research methodology that was used

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

This chapter outlines the research methodology for obtaining the data to answer the research questions. It details the research methods, study population, and sampling techniques adopted. The research methodology used is primarily influenced by the research questions and the type of data that needs to be collected to respond adequately to the research questions identified. The chapter first discusses the research approach, followed by research design, population and sampling, data collection, data analysis, and validity and reliability.

3.2 Research Approach

A research approach is a procedural plan adopted by the researcher to answer research questions validly, objectively, accurately and economically (Kumar, 2015). The approach followed in this study is quantitative, with a post-positivist interpretation, to statistically understand and infer the relationships between factors that influence chatbot engagement on customer experience and frustrations in self-help functions. Quantitative research involves gathering and analysing numerical data to understand the perspectives and experiences of respondents (Saunders et al., 2019). According to Leedy and Ormrod (2015), quantitative research aims to explain, forecast, and regulate phenomena by answering queries regarding correlations among measured variables. Quantitative research relies on empirical information collected, organised, and statistically analysed to examine the relationship between variables using a deductive approach (Moises, 2020). Quantitative research collects data through surveys and analyses using statistical approaches (Sheard, 2018).

In utilising a post-positivist philosophy for this study on the antecedents of customer chatbot engagement and its impact on satisfaction and frustration, the research paradigm acknowledges the objective nature of the phenomena under investigation (Creswell & Creswell, 2017). While emphasising the importance of measurable variables and statistical analyses, the post-positivist approach within the quantitative framework recognises that interpretations and perceptions may still shape user responses (Creswell & Creswell, 2017). This approach allows for identifying patterns and relationships through statistical methods, providing valuable insights into the relationships posited by the UTAUT model. Adopting a post-positivist perspective within a quantitative paradigm underscores the acknowledgement of the complexity inherent in human-technology interactions, even within the structured realm of quantitative research.

3.3 Research design

This study employed a causal research design to investigate the relationship between the identified antecedents of customer chatbot engagement and the subsequent impact on satisfaction and frustration. Causal research aims to establish cause-and-effect relationships between variables, allowing for an in-depth exploration of how changes in one variable influence another (Creswell & Creswell, 2017). This study sought to determine the causal linkages implied by the UTAUT model, examining the extent to which factors such as perceived ease of use, performance expectancy, social influence, and compatibility contribute to engagement and the subsequent effect on variations in customer satisfaction and frustration. The causal research design was chosen to provide a systematic approach, enabling the identification of critical drivers of customer chatbot engagement and their downstream effects on user satisfaction and frustration.

A closed-ended survey was designed to collect data. Surveys have the following advantages and disadvantages (Lindemann, 2023):

Table 2: Advantages and disadvantages of surveys

Advantages	Disadvantages
It easily enables a wider population reach.	Lack of depth: Not being able to observe customers' reactions when they answer the questionnaire

Low to no cost to the researcher or the institution	Respondents may misinterpret the questionnaire.
The ability to quantify the questionnaire's responses using statistical methods is more effortless.	Researcher prejudice in the creation of questionnaires
Ease of data collection and analysis	Potential for lack of validity if the instrument is not adequately tested
The best way to test a hypothesis	
Comparing data analysis to other research methods, this method is more objective and scientific.	

3.4 Population and sample

3.4.1 Population

The population is defined as a group of units subjected to research where a study is conducted and findings documented (Shukla, 2020). The target population for this study comprised individuals who have interacted with a chatbot from South African telecommunications companies. To ensure geographical representation and manageability, the study largely included students from Wits University, assuming that these students come from various regions across South Africa and have engaged with chatbots from any telecommunications company within the country. In addition, individual from across South Africa were also part of the target population. This approach enabled a comprehensive analysis of chatbot engagement within the telecommunications sector while leveraging a diverse and accessible sample population. It was however difficult to get the total number of chatbot users with the South African telecommunications industry. Therefore, the population size was unknown in this study.

3.4.2 Sample and sampling method

A sample is a small portion of a group of data subjects to be drawn from a population. Sampling is a method researchers use to infer information regarding a population based on research findings from a sample (Rahman et al., 2022). According to Acharya et al. (2013), the probability sampling method is the most effective quantitative research method. Probability sampling is based on a random sampling method, which allows for reduced sampling bias as participants are selected randomly (Creswell & Creswell, 2017). However, probability sampling requires a known population size. In this study, the population size was unknown, suggesting that non-probability sampling methods were appropriate (Flick, 2018).

Non-probability sampling refers to a sampling technique where the samples are gathered in a process that does not give all individuals in the population an equal chance of being selected (Flick, 2018). One common form of non-probability sampling is convenience sampling, where participants are selected based on their availability and willingness to take part in the study. In a situation where there is no known population size, convenience sampling is justified as it allows researchers to gather data quickly and efficiently from those who are readily available to respond (Creswell & Creswell, 2017).

Screening questions were subsequently applied to identify and select only those participants who had engaged with chatbots, refining the sample to those relevant to the study's objectives. While random sampling is ideal for generalisability, the convenience sampling approach was pragmatic, allowing for a more feasible and inclusive survey process. When sending a survey online, using convenience sampling means that the sample size was determined by the number of responses received, making it practical and feasible under constraints of time and resources. In this study, 412 responses were received from the survey. However, following data screening, the final sample size of this study was 258.

3.5 Data collection methods

A survey questionnaire was designed to gather data for this research paper. A survey measures knowledge, constructs, practices, or behaviour in a study. (David et al., 2019). The questionnaire consisted of simple questions intentionally made easy for the respondent to understand. The questions were intentionally created to allow the respondents to share their perceptions of their satisfaction with Chatbot as customer service agents and any frustrations experienced during their engagements with Chatbots as customer service agents. Close-ended questions were selected to simplify the analysis portion of the research paper and enhance the respondents' response rate (David et al., 2019). A short, simple, straight-to-the-point self-administered survey questionnaire was put together to avoid a long-winded survey that might deter respondents from completing it. This is because most web users spend less time on a page when browsing a website (David et al., 2019).

This study used an online survey questionnaire designed using Qualtrics. A web link containing the electronic questionnaire was distributed to respondents between 18 and 65. The questionnaire targeted respondents who have used chatbots before to analyse their perceived experiences and outputs. Emails were sent to the undergraduate and postgraduate students at the University of Witwatersrand to participate in the survey. The link was also shared on various platforms, such as LinkedIn and WhatsApp groups, encouraging students to share with others across different platforms. Additionally, the link was posted on the author’s Facebook status and page posts with a request for respondents to participate and share the survey.

3.6 The research instrument

The questionnaire was designed to collect data on the demographic profiles of respondents and the questions that addressed the hypotheses stated in this study. The questionnaire began with a page that introduced the research topic and requested consent. A brief description explaining what a chatbot is with examples was provided, and a qualification question was presented to the respondent to gather data from viable. An assurance statement of confidentiality and anonymity to the respondents was part of the definition to gain the respondents’ trust.

To ensure survey respondents had the necessary knowledge of chatbots, a screening question about respondents' experience with the concept was added in the first section. This ensured that only those who have used chatbots participated in the study. Participants' Demographic information was also collected, focusing on the gender and age of respondents.

The research instrument was meant to collect ratings of perceptions, compatibility, intentions, and engagement of chatbots as self-help tools. The questionnaire had structured closed-ended and Boolean choice questions. Users were asked about their perceptions using the five Likert scale dimensions in the study questionnaire. Rensis Likert created the Likert scale. According to Huang and Liaw (2005), Likert-type questions best assess users' attitudes, feelings, and experiences. A 5-point Likert scale was then used, ranging from strongly disagree to agree strongly. The scale was as follows: Strongly Disagree=1, Disagree=2, Neither Agree nor Disagree=3, Agree=4 and Strongly Agree 5 points. The intentional section of the survey also measures on a 5-point scale where 1 = Very Unlikely, 2= = Unlikely, 3= = Neutral, 4=Likely, and 5= = Very Likely.

The scales used to measure the dimensions of the various variables were adapted from the literature. The design of the questionnaire, in line with the hypothesis that each section intended to answer, is summarised in Table 3~~Table 3~~.

Table 3: Data collection to Hypothesis traceability

Variable Name	Research Question/ Hypothesis	Source	Item on survey
Perceived ease of Use (PEOU)	(H1) Perceived ease of use positively influences customer chatbot engagement.	Venkatesh et al. (2012).	Questions 9,10,11,12
Performance expectancy (PE)	(H2) Performance expectancy positively influences customer chatbot engagement.	Venkatesh et al. (2012)	Questions 31,32,33,34
Compatibility (CO)	(H3) Perceived compatibility positively influences chatbot engagement quality.	Casais et al. (2020); Alt et al. (2021).	Questions 5,6,7,8
Social Influence (SI)	(H4) Perceived social influence positively affects customer chatbot engagement.	Josh (2021); Gopinath and Kasilingam (2023).	Questions 17,18,19,20,21
Dependent Variable: Customer Satisfaction	(H6) Customer chatbot engagement positively influences the overall customer experience.	George and Kumar (2014); Camilleri and Filieri (2023).	Questions 22,23,24,25,26
Dependent variable: Customer Frustration	(H7) Customer chatbot engagement reduces customer frustration.	Huang and Dootson (2022)	Questions 27,28,29,30

3.7 Data analysis strategies and interpretation

The data was analysed using IBM's Statistical Package for Social Sciences (SPSS) tool provided by Wits Business School. The data analysis procedure commenced with an exploration of respondents' demographics to establish the representativity of the sample. Following the demographic analysis, the reliability of the scales used in the study was assessed using Cronbach's alpha. This statistical measure gauges the internal consistency of items within each construct (Field, 2018). An Exploratory Factor Analysis (EFA) was conducted to unravel the underlying structure of the data. EFA is a robust technique for identifying latent factors contributing to observed patterns in the data (Field, 2018). This step was crucial for confirming the presence of the factors postulated by the UTAUT model, offering insights into the interrelationships among variables and guiding the creation of composite scales.

Once the factors were confirmed through EFA, composite scales were computed, combining relevant items to form cohesive constructs representing the identified factors. These composite scales facilitated a more concise representation of the theoretical constructs and ensured a focused analysis of the hypotheses.

The analysis then focused on descriptive statistics, correlation analyses, and multiple linear regression models to test the formulated hypotheses. Descriptive statistics provided a summary of the main features of the dataset, while correlation analyses explored the relationships among the variables. Multiple linear regression models were estimated to examine the impact of antecedents on customer chatbot engagement and subsequent satisfaction and frustration.

The p-value approach was employed to assess the significance of the regression coefficients in testing the hypotheses. A significance level ($p = 0.05$) was used to determine whether the relationships between the independent and dependent variables were statistically significant. A lower p-value indicated more substantial evidence against the null hypothesis, supporting the validity of the proposed relationships.

3.8 Quality Assurance

3.8.1 External validity

External validity in this study was ensured through several key measures. Firstly, the study employed systematic random sampling for sample selection, allowing for broader generalisability. This method enables any organization or entity considering implementing other customer service tools to use the research findings as a guide or apply them directly to assess the relevance of the study outcomes to their specific context.

Furthermore, the study prioritised transparent reporting, ensuring transparency in presenting research methodology and outcomes. Transparent reporting is crucial for facilitating other researchers' assessment of how well the study's findings align with their contexts. This commitment to clarity in reporting allows for a comprehensive evaluation of the research, irrespective of whether the outcomes are favourable or unfavourable, following established research practices (Polit & Beck, 2010). Overall, these measures collectively contributed to the study's external validity, enhancing its relevance and applicability beyond the immediate research context.

3.8.2 Internal validity

Internal validity in this study was ensured by conducting EFA. EFA ensured a rigorous examination of the underlying structure of the data and the interrelationships among variables. This analytical approach allowed for identifying and confirming factors postulated by the UTAUT model, contributing to establishing a solid internal structure within the study. EFA's ability to uncover latent constructs and reduce dimensionality ensured that the variables measured were representative of the intended theoretical constructs (Surucu & Maslakci, 2020).

3.8.3 Reliability

To ensure the reliability of the questionnaire, Cronbach's Alpha was employed to assess the sample's internal consistency. This widely used statistical measure, ranging from 0.0 to 1.0, quantifies the degree to which items on an instrument are correlated, with values exceeding 0.7 indicating approximately 70% consistency (Adamsson & Prion, 2013). A score of 0.7 or higher was deemed ideal, signifying a greater likelihood of stable and reliable results when administering the questionnaire under consistent conditions. This approach ensured that the questionnaire exhibited robust internal consistency, reinforcing the reliability of the research instrument.

3.9 Ethical considerations

This study adhered to ethical considerations to ensure the responsible and respectful treatment of study participants. All respondents were treated with due respect and consideration throughout the research process. An informed consent approach was employed, ensuring respondents were fully aware of the research purpose before engaging. To safeguard individual confidentiality and anonymity, no personally identifiable information was collected. The study specifically targeted individuals above 18 years of age, excluding any age range below this threshold in the demographic section of the questionnaire.

In line with academic integrity, the paper is plagiarism-free, accurately reflecting the results derived from data analysis. Respondents were granted the right to withdraw from the study by utilising the close button on the survey page, emphasizing voluntary participation. Transparency was maintained by avoiding any misleading information, and the participation letter openly communicated the core purpose of the research.

Ethical clearance was obtained from the Wits University Business School Postgraduate Committee (PGC) before the commencement of data collection, ensuring institutional approval. Data were securely stored on a password-protected Google Drive for the required study period, and access is available upon request. Results were reported truthfully and accurately, meeting validity and reliability requirements, even in cases where they deviated from the researcher's initial perspective. The reporting of findings prioritized honesty, avoiding any suppression of opinions or fabricating statistics to align with specific viewpoints, thereby upholding the ethical standards throughout the research process.

3.10 Chapter summary

This study, anchored in a post-positivist paradigm, adopted a quantitative approach and employed a causal research design to investigate the antecedents of customer chatbot engagement and their impact on satisfaction and frustration. In targeting users of chatbots, a convenience sampling approach was utilised. An online survey was distributed, capturing user perspectives on chatbot interactions. Data analysis included regression analysis, exploring the relationships between identified factors and user outcomes. The study prioritised data quality by testing reliability through Cronbach's Alpha and ensuring internal validity through Exploratory Factor Analysis (CFA). Ethical considerations were integral, with the study obtaining clearance from the Wits University Business School Postgraduate Committee and implementing safeguards like informed consent, confidentiality, and the right to withdraw. The next chapter presents the results of the study.

CHAPTER 4

PRESENTATION OF RESULTS / FINDINGS

4.1 Introduction

This chapter aims to present results from the collected data from a survey of chatbot users. Demographic profiles of respondents are presented and discussed in the first section of the chapter. The second section focuses on the analysis of the research instrument, analysing the reliability and validity of the measurement scales employed in the study. Furthermore, descriptive statistical analysis of the questions is conducted, followed by normality tests. This is followed by correlation analysis, assessing the strengths and direction of the relationship among the variables. Multiple linear regression analysis is then conducted to test the hypotheses formulated. Lastly, a chapter summary is presented, focusing on whether or not the hypotheses were supported.

4.2 Demographics profile of respondents

Data was collected from South Africans who have used chatbots as a self-help function within the context of telecommunications companies. A link to the survey was published so that respondents could access the survey, and responses were automatically corrected for data analysis by Qualtrics. Four hundred and twelve (412) responses were received, and the data was downloaded as an Excel file and cleaned for further analysis. The data cleaning process revealed that 154 responses were incomplete and were, therefore, removed. Only 258 responses were complete, which is 62% of the total responses received. Accordingly, the final sample for this study comprised of 258 respondents.

4.2.1 Age and gender

Demographic information collected in this study includes the age group of respondents and gender. Table 4~~Table 4~~ provides a summary of respondents' demographic information.

Table 4: Demographical Information

Variable	Category	Frequency	Percentage
Gender	Male	102	39.5%
	Female	153	59.3%
	Non-Binary/ Third gender	1	.4%
	Prefer Not to Say	2	.8%
Total		**258**	**100%**
Age	18-24 years	42	16.3%
	25-34 years	71	27.5%
	35-44 years	105	40.7%
	45-54 years	33	12.8%
	55 years and above	7	2.7%
Total		**258**	**100%**

The gender distribution in the sample shows that the majority were female respondents (59.3%), followed by male respondents (39.5%). The representation of non-binary/third-gender individuals and those who preferred not to disclose is relatively small, making up 0.4% and 0.8% of the sample, respectively.

The age distribution in the sample indicates a relatively balanced representation across different age groups. Most respondents fall into the 35-44 age group (40.7%), followed by the 25-34 age group (27.5%). The 18-24 years and 45-54 age groups represent 16.3% and 12.8%, respectively, while respondents aged 55 and above comprise 2.7% of the sample.

4.2.2 Frequency of use of chatbot

The study sampled only those respondents who have previously used chatbots. In addition, the study also collected data on the frequency of use of these chatbots. Table 5~~Table 5~~ summarises the sample distribution in terms of frequency of chatbot use.

Table 5: Frequency of chatbot use

How frequent	Frequency (n)	Percentage (%)
Rarely	110	42.6%
Occasionally	48	18.6%
Frequently	90	34.9%
Very frequently	10	3.9%
Total	**258**	**100.0**

Table 5~~Table 5~~ shows that regarding chatbot usage frequency, 42.6% reported rare use, 18.6% occasional use, 34.9% frequent use, and 3.9% widespread use. These findings highlight varying engagement levels with chatbots, emphasising the importance of considering user preferences and experiences in optimising chatbot design for practical self-help functions among customers in South Africa.

4.3 Analysis of measurement scales

The measurement scales employed in this study were assessed for reliability and validity using Cronbach's alpha and factor analysis, respectively. Firstly, a reliability analysis was conducted to assess the internal consistency of the scales used. Factor analysis was then conducted to ascertain the extent to which the items within a particular scale measured what they were intended to measure.

4.3.1 Reliability analysis

The reliability of the scale was assessed using Cronbach's alpha. Cronbach's alpha coefficient was calculated for each scale to assess the extent of internal consistency of the measurement scale. Table 6~~Table 6~~ provides a summary of the cut-off ranges for different levels of internal consistency.

Table 6: Levels of internal consistency

Cronbach's Alpha	Internal Consistency
$\alpha \geq 0.9$	Excellent
$0.8 \leq \alpha < 0.9$	Good
$0.7 \leq \alpha < 0.8$	Acceptable
$0.6 \leq \alpha < 0.7$	Questionable

0.5 ≤ α < 0.6	Poor
α < 0.5	Unacceptable

Source: Adapted from Cronbach (1951)

The constructs assessed for internal consistency is this study include Perceived Ease of Use (PEOU), Performance Expectancy (PE), Compatibility (CO), Social Influence (SI), Customer-Chatbot Engagement (CCE), Customer Satisfaction (CS), and Customer Frustration (CF). Table 7~~Table 7~~ summarises the constructs' reliability analysis, showing the original number of items per scale, the items removed after adjustment, the final number of items measured, Cronbach's alpha, and the conclusion guided by the criteria in Table 6~~Table 6~~.

Table 7: Summary of reliability analysis

Scale	Number of items per scale	Items removed after the reliability test	The final number of items measured	Cronbach Alpha after adjustment	Reliability conclusion
Perceived Ease of Use (PEOU)	4	0	4	0.853	Good
Performance Expectancy (PE)	4	0	4	0.941	Excellent
Compatibility (CO)	4	0	4	0.749	Acceptable
Social Influence (SI)	5	0	5	0.814	Good
Customer-Chatbot Engagement (CCE)	4	1 (CCE4)	3	0.771	Good

Scale	Number of items per scale	Items removed after the reliability test	The final number of items measured	Cronbach Alpha after adjustment	Reliability conclusion
Customer Experience (CX)	5	0	5	0,853	Good
Customer Frustration (CF)	4	0	4	0,651	Questionable

Source: Primary data

The reliability analysis results, as presented in Table 7~~Table 7~~, indicate different levels of internal consistency for the assessed constructs. All scales demonstrated acceptable to excellent reliability, with Cronbach's alpha values ranging from 0.749 to 0.941, meeting the criteria outlined in Table 7~~Table 7~~. Notably, for the customer-chatbot engagement (CCE) scale, the removal of one item (CCE4) led to an improvement in Cronbach's alpha from 0.517 to 0.771, reaching a "Good" level of internal consistency. This adjustment underscores the importance of scrutinising individual items to enhance the reliability of the measurement instrument.

However, the customer frustration (CF) scale exhibited a lower Cronbach's alpha of 0.651, falling into the "Questionable" range. The low Cronbach's alpha might be attributed to the fact that this scale is a novel contribution to the study, with items devised independently due to the absence of prior studies employing the construct. The challenge of creating a new scale lies in achieving high internal consistency, and the initial alpha value suggests a need for further refinement. The diverse nature of customer frustration and the inherent difficulty in capturing it comprehensively could have contributed to the lower reliability.

Overall, the measurement scales demonstrated internal consistency and were further scrutinised for validity, as discussed in the following section.

4.3.2 Validity analysis

The study employed exploratory factor analysis (EFA). To evaluate both convergent and discriminant validity. This statistical technique allowed for an in-depth examination of the relationships between variables, helping to identify patterns of shared variance (convergence) among items measuring the same construct and distinctions between constructs (discrimination). EFA facilitated an understanding of how well the measurement instrument aligns with theoretical expectations, providing insights into the validity and structure of the constructs under investigation.

A sample adequacy test was first conducted to assess the adequacy of the sample to conduct EFA. The Kaiser-Meyer-Olkin Measure of Sampling Adequacy and Bartlett's Test of Sphericity were conducted. Table 8~~Table 8~~ shows the results.

Table 8: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.928
Bartlett's Test of Sphericity	Approx. Chi-Square	4470.011
	Df	406
	Sig.	.000

Source: Primary data

The sample size is adequate for EFA if the KMO statistic is at least 0.5 and the Bartlett test statistic is statistically significant (Field, 2018). As shown in Table 8~~Table 8~~, the KMO value of 0.928 suggests a high degree of sampling adequacy, indicating that the sample was suitable for factor analysis. Additionally, Bartlett's Test of Sphericity, with a significant chi-square value of 4470.011 ($p < 0.001$), supports the presence of relationships among variables, further justifying the appropriateness of the sample for conducting EFA. Overall, these results provide confidence in the adequacy of the dataset for the subsequent factor analysis.

Determining the number of factors to extract is crucial in the second step. In this study, the decision was guided by both statistical criteria and visual inspection. Kaiser's criterion, which involves extracting factors with eigenvalues greater than 1, was utilised. Additionally, the scree plot, a graphical representation of eigenvalues, was inspected to identify the point at which the eigenvalues plateau, indicating the appropriate number of factors to retain. These methods help avoid over-extraction of factors. The study chose Principal Axis Factoring (PAF) as the extraction method, given its preference in social sciences. PAF considers common and unique factors (error), providing a more nuanced understanding of the underlying structure of the constructs being analysed (Field, 2018). This approach aligns with the exploratory nature of the factor analysis in uncovering the latent factors within the data. Figure 2~~Figure 2~~ shows the scree plot.

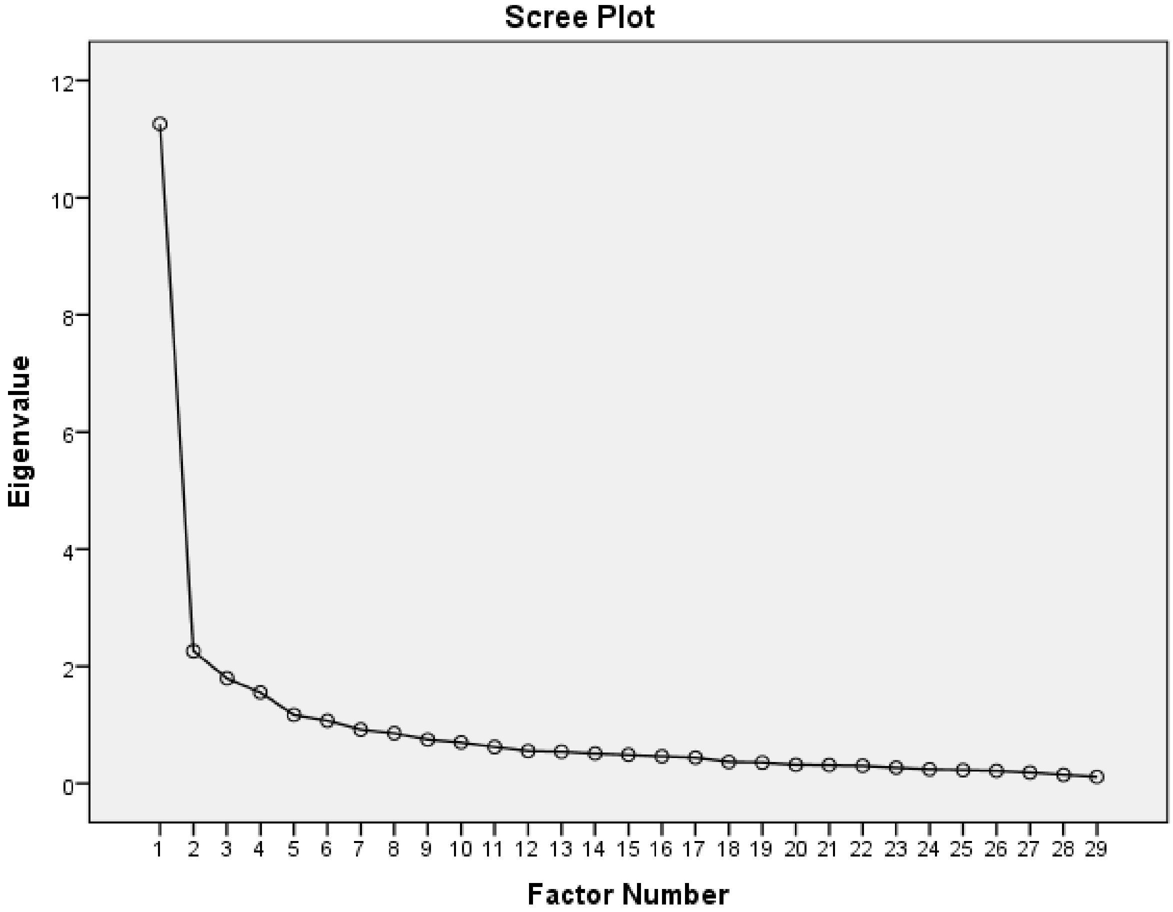

Figure 2: Scree plot

Source: Primary data

Figure 2~~Figure 2~~ shows seven small dots above the eigen value of 1. Therefore, seven factors were extracted in this study using PAF.

After factor extraction, factor rotation was performed. Factor rotation is a crucial step in EFA that aims to simplify the interpretation of the factors by maximising the variance of loadings within factors. In this study, Promax was employed as the rotation method. Promax is an oblique rotation technique that allows factors to be correlated, acknowledging that in real-world situations, factors are often not wholly independent (Field, 2018). Utilising Promax rotation suggests that the study acknowledges potential correlations between factors, providing a more realistic representation of the relationships among constructs. This method facilitates a more straightforward and meaningful interpretation of the factors, as it allows for more flexibility in positioning items across factors (Field, 2018). Table 9~~Table 9~~ shows the rotated factor matrix, the extracted factors, the items, and the loadings.

Table 9: Rotated factor matrix

Pattern Matrix							
	Factor						
	PE (1)	PEOU (2)	SI (3)	CS (4)	CO (5)	CF (6)	CCE (7)
CO2					.498		
CO3					.653		
CO4					.518		
PEOU1		.706					
PEOU2		.795					
PEOU3		.662					
PEOU4		.704					
PE1	.904						
PE2	.878						
PE3	.894						
PE4	.785						
SI1			.633				
SI2			.592				
SI3			.438				
SI4			.809				
SI5			.912				
CS1				.723			
CS2				.550			
CS3				.701			
CS4				.624			
CF1						.509	
CF2						.728	
CF3						.511	

CF4						.606	
CCE1							.816
CCE2							.707
CC2							.562
Extraction Method: Principal Axis Factoring. Rotation Method: Promax with Kaiser Normalization.							
a. Rotation converged in 8 iterations.							

Source: Primary data

In the rotated factor matrix (Table 9~~Table 9~~), items with factor loadings of at least 0.4 were retained. The decision to set a cut-off for factor loadings at 0.4 was justified to ensure that only items with meaningful contributions to a factor were retained. A factor loading of 0.4 or higher indicates that the underlying factor accounts for 40% of the variance in an item, providing a reasonable threshold for retaining items (Field, 2018).

Items with low factor loadings were removed; for example, CS5 had a low factor loading (0.342) and was removed, leaving the customer satisfaction factor (CS) with only four items. Additionally, the item CO1 had high loadings on three different factors and was removed due to cross-loading. This meticulous approach ensured the retention of items that distinctly contributed to their intended factors. Therefore, only three compatibility factor (CO) items were retained.

The retained items demonstrated high factor loadings on their respective factors, supporting convergent validity. For instance, all items related to perceived ease of use (PEOU), performance expectancy (PE), social influence (SI), customer satisfaction (CS), customer-chatbot engagement (CCE), and customer frustration (CF) exhibited factor loadings above 0.4, indicating convergent solid validity within each construct.

Overall, the rotated factor matrix revealed a well-defined factor structure with high loadings for retained items. The removal of CS5 and CO1 contributed to the overall validity of the measurement instrument. The results indicated satisfactory convergent validity within each construct and suggested distinct factors with minimal overlap.

4.4 Descriptive statistics

After factor analysis, composite variables were derived for each factor by computing each construct's average scores of the constituent items. This process involved summing the scores of individual items and dividing by the total number of items within a specific factor. This resulted in composite scales representing PEOU, PE, SI, CS, CCE, and CF. Using composite variables facilitated a more streamlined and manageable representation of each construct, reducing the complexity of handling individual items. These composite scales, reflective of the underlying factor structures identified through factor analysis, were subsequently employed in further statistical analyses, including descriptive statistics, normality tests, correlation assessments, and regression analyses.

Descriptive statistics for the constructs are presented in Table 10~~Table 10~~.

Table 10: Descriptive statistics

Construct	N	Mean	Std. Deviation
PEOU	258	3.94	.93
PE	258	3.33	1.15
CO	258	3.80	.76
SI	258	3.06	.85
CCE	258	2.67	.86
CS	258	3.58	.94

CF	258	3.78	.88

Source: Primary data

The descriptive statistics (Table 10~~Table 10~~) provide insights into the respondents' perceptions across the different constructs. For PEOU, the mean of 3.94 suggests that, on average, respondents agreed with statements about the ease of using the chatbot, indicating a favourable perception. The relatively low standard deviation (SD = 0.93) indicates a moderate level of agreement and a consistent trend among respondents. Performance expectancy (PE) yielded a mean of 3.33, suggesting a moderate agreement with performance-related statements, while a higher standard deviation (SD = 1.15) indicates more variability in responses. Compatibility (CO) achieved a mean of 3.80, indicating agreement with compatibility-related statements, with a low standard deviation (SD = 0.76) suggesting a more consistent consensus among respondents. Social Influence (SI) had a mean of 3.06, suggesting a moderate level of agreement, and a standard deviation of 0.85 reflects some variability in responses. Customer-Chatbot Engagement (CCE) received a mean of 2.67, indicating a somewhat lower level of agreement, and the standard deviation of 0.86 suggests varied responses. Customer Satisfaction (CS) had a mean of 3.58, indicating a generally positive sentiment, with a moderate standard deviation (SD = 0.94) signifying some variability. Lastly, Customer Frustration (CF) demonstrated a mean of 3.78, indicating a tendency toward agreement with frustration-related statements, while a standard deviation of 0.88 suggests some variability in responses.

4.5 Normality Tests

Normality tests were conducted using the Kolmogorov-Smirnov and Shapiro-Wilk tests, as shown in Table 11~~Table 11~~.

Table 11: Normality Tests

Construct	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	Df	Sig.	Statistic	df	Sig.

PEOU	.170	258	.000	.881	258	.000
PE	.153	258	.000	.935	258	.000
CO	.152	258	.000	.930	258	.000
SI	.091	258	.000	.986	258	.014
CCE	.127	258	.000	.960	258	.000
CS	.130	258	.000	.956	258	.000
CF	.132	258	.000	.930	258	.000
a. Lilliefors Significance Correction						

Source: Primary data

Normality tests were conducted to determine data distribution and guide the choice between parametric or non-parametric tests for further analyses. The significance level for all tests was set at 0.05. The Kolmogorov-Smirnov results indicated that all constructs (PEOU, PE, CO, SI, CCE, CS, and CF) had significant p-values of .000, suggesting non-normal distributions. Similarly, Shapiro-Wilk tests also yielded significant p-values of .000 for all constructs. The results indicate that the data did not meet the assumption of normality. As a result, non-parametric tests are more appropriate for subsequent analyses, considering the non-normal distribution of the data across all constructs.

4.6 Correlation analysis

Since the data is not normally distributed, Spearman's rank correlation coefficient (Spearman's rho) was appropriate for correlation analysis in this study. Spearman's rho is a non-parametric measure of correlation that assesses the strength and direction of the monotonic relationship between two variables (Field, 2018). Unlike Pearson correlation, Spearman's rho does not assume normality and is robust to outliers. Table 12~~Table 12~~ provides a summary of the correlation analysis conducted.

Table 12: Correlation analysis

Variable	CCE	PEOU	PE	CO	SI	CS	CF

CCE	1.000						
PEOU	.648**	1.000					
PE	.558**	.682**	1.000				
CO	.354**	.535**	.599**	1.000			
SI	.541**	.573**	.554**	.410**	1.000		
CS	.583**	.633**	.711**	.593**	.565**	1.000	
CF	-.309**	-.251**	-.188**	-.144*	-.202**	-.193**	1.000

***. Correlation is significant at the 0.01 level (2-tailed).*

**. Correlation is significant at the 0.05 level (2-tailed).*

Source: Primary data

Spearman's rho correlation analysis (Table 12~~Table 12~~) reveals several significant associations among the variables. Notably, a positive correlation is observed between CCE and PEOU (ρ = 0.648, $p < 0.01$), suggesting that users who find the chatbot easy to use are likelier to engage with it. Similarly, positive correlations are found between CCE and other variables such as PE, CO, SI, and CS. However, the correlation between CF and other variables, including CCE, is negative. This implies that as frustration increases, engagement tends to decrease.

Additionally, the correlations among independent variables (PEOU, PE, CO, SI) are less than 0.8, indicating that multicollinearity issues are not severe. This is crucial for regression analysis, as high correlations among predictors can lead to multicollinearity, affecting the stability and interpretability of regression coefficients (Field, 2018). The observed correlations support the consideration of these variables in subsequent analyses, providing insights into the interrelationships within the studied constructs.

4.7 Multiple Linear Regression

A linear regression model should satisfy certain assumptions for the results to be valid. Key assumptions include linearity, homoscedastic variance, and customarily distributed residual. The linearity assumption states that the model must be specified as a linear function. This assumption was tested using the correlation matrix presented in Table 12~~Table 12~~, which shows that the dependent variable (CCE) has significant linear relationships with all the independent variables (PEOU, PE, CO, SI). There are also significant linear associations between CS and CCE and CF and CCE. This confirms the linearity assumption (Field, 2018).

The model with CCE as the dependent variable was tested for homoscedastic assumption using a scatterplot of standardised versus predicted residual. This is shown in Figure 3~~Figure 3~~.

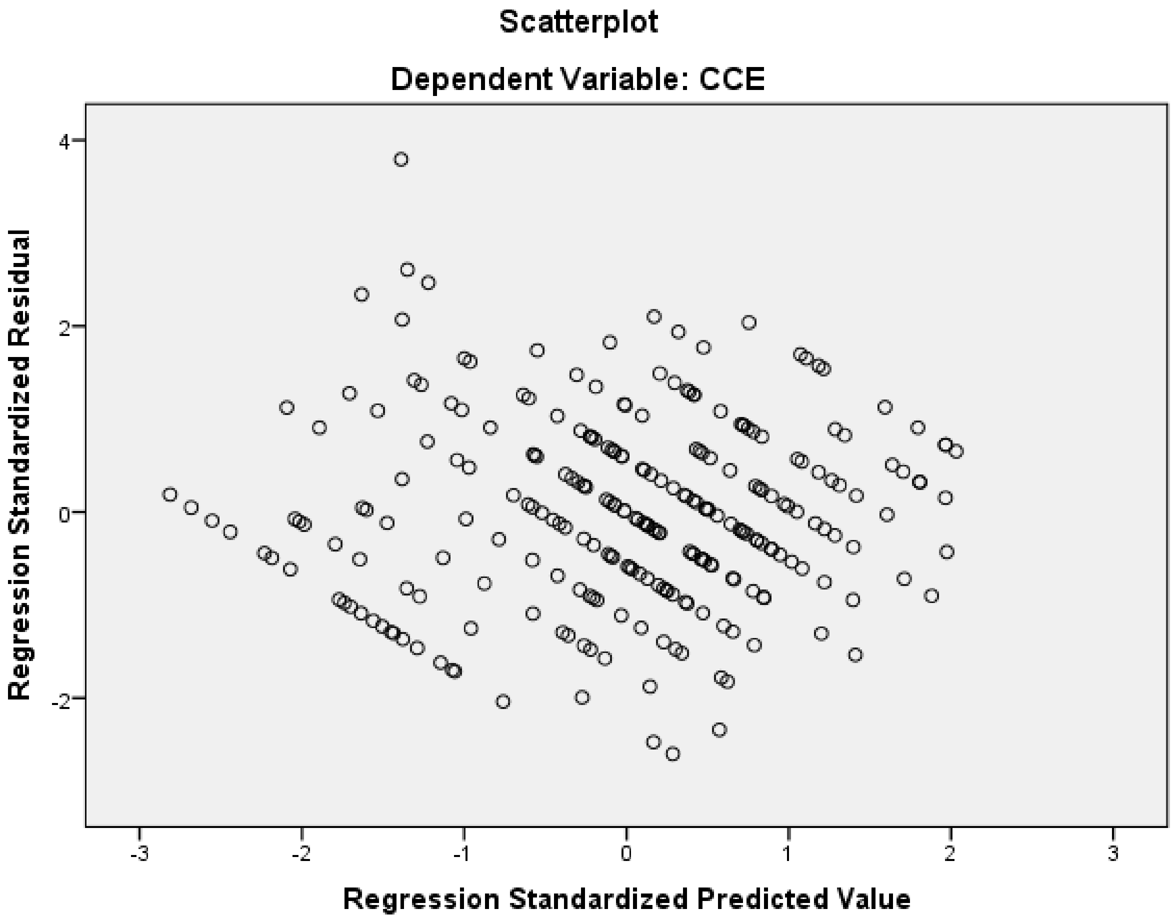

Figure 3: Heteroskedasticity Test

Source: Primary data

Visual inspection of the plot of residuals shows that all the residuals are within the range of -3 to +3, suggesting no heteroskedasticity (Field, 2018).

Further, a Normal P-P plot was used to test for residual normality, as shown in Figure 4~~Figure 4~~.

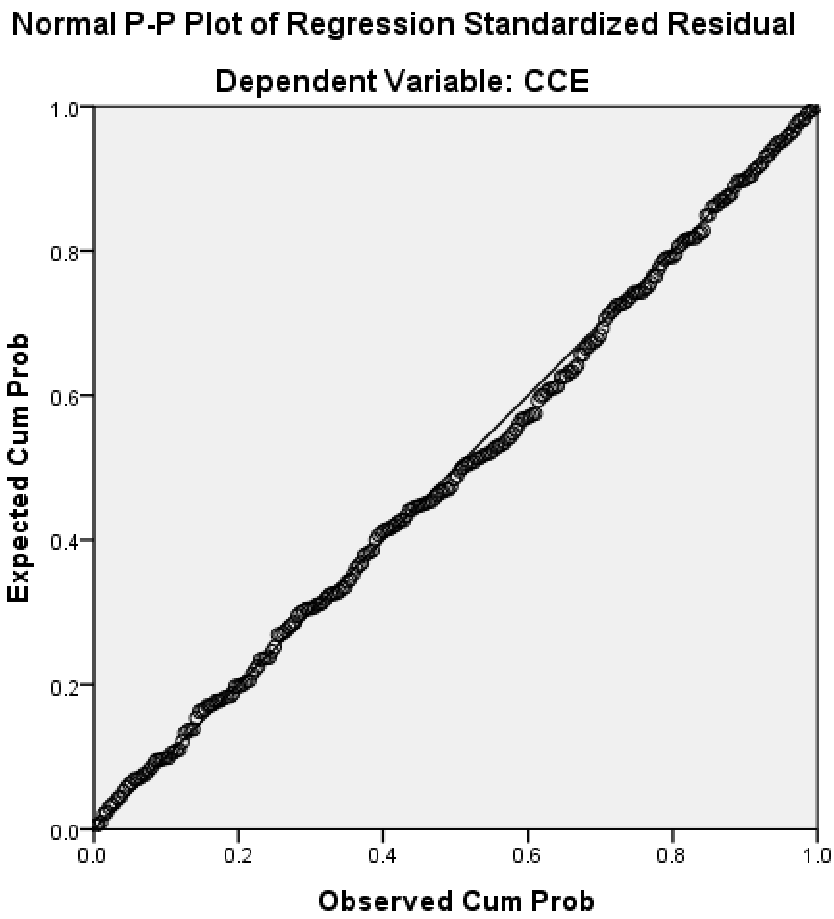

Figure 4: Normality Test

Source: Primary data

Figure 4~~Figure 4~~ shows that the probability plot is on the diagonal line, and there is no significant deviation from the diagonal line. This suggests that the residuals were normally distributed (Field, 2018).

Therefore, regression model assumptions were satisfied, and the model results are presented in the following section.

4.7.1 Antecedents of customer chatbot engagement

The first multiple linear regression model was estimated to analyse the antecedents of customer chatbot engagement. The dependent variable was customer chatbot engagement (CCE), and the independent variables were PEOU, PE, CO, and SI. The model summary is given in Table 13~~Table 13~~.

Table 13: Model Summary: Antecedents of customer chatbot engagement

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.738[a]	.545	.538	.58248
a. Predictors: (Constant), SI, CO, PE, PEOU				

Source: Primary data

The R-square value of 0.545 indicates that approximately 54.5% of the variability in customer chatbot engagement is explained by the included independent variables (PEOU, PE, CO, and SI). The adjusted R-square, accounting for the number of predictors, remains relatively high at 0.538. The significant R and R-square values suggest that the chosen predictors collectively contribute to explaining the variance in customer chatbot engagement—Table 14~~Table 14~~ shows the validity of the whole model.

Table 14: ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	102.827	4	25.707	75.768	.000[b]
	Residual	85.838	253	.339		
	Total	188.665	257			
a. Dependent Variable: CCE						

b. Predictors: (Constant), SI, CO, PE, PEOU

Source: Primary data

The F-test results in Table 14~~Table 14~~ indicate the overall validity of the multiple linear regression model assessing the antecedents of customer chatbot engagement. The highly significant F-value of 75.768 ($p < 0.001$) suggests that the regression model is statistically significant. This implies that at least one of the independent variables (SI, CO, PE, PEOU) significantly contributes to predicting customer chatbot engagement (CCE). Therefore, the model is deemed valid, and including the specified predictors provides meaningful explanatory power for understanding the variability in customer chatbot engagement.

Table 15: Regression coefficients

Model		**Unstandardized Coefficients**		**Standardized Coefficients**	**T**	**Sig.**
		B	**Std. Error**	**Beta**		
1	(Constant)	.332	.197		1.685	.093
	PEOU	.480**	.063	.495	7.644	.000
	PE	.136**	.047	.182	2.893	.004
	CO	.168**	.063	.150	2.665	.008
	SI	.268**	.056	.265	4.821	.000
Dependent Variable: CCE						
***. Coefficient is significant at the 1% level*						

Source: Primary data

Results in Table 15~~Table 15~~ show that all four variables significantly and positively influence customer chatbot engagement.

4.7.2 Customer chatbot engagement and customer satisfaction

The study further assessed whether customer chatbot engagement affects customer satisfaction with using the chatbot. A simple linear regression model was estimated, with customer satisfaction as the dependent variable and chatbot engagement as the independent variable. The model summary is provided in Table 16~~Table 16~~.

Table 16: Model summary: CCE and CS

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.606[a]	.367	.364	.74579
a. Predictors: (Constant), CCE				

Source: Primary data

The R-square value of 0.367 suggests that approximately 36.7% of the variability in customer satisfaction can be explained by the chatbot engagement level.

Table 17: ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	82.526	1	82.526	148.373	.000[b]
	Residual	142.389	256	.556		
	Total	224.916	257			
a. Dependent Variable: CS						
b. Predictors: (Constant), CCE						

Source: Primary data

The F-test for overall validity in Table 17~~Table 17~~ indicates that the simple linear regression model assessing the impact of customer chatbot engagement (CCE) on customer satisfaction (CS) is highly significant. The F-value of 148.373 ($p < 0.001$) suggests the regression model is statistically valid. This implies that including chatbot engagement as a predictor significantly contributes to explaining the variance in customer satisfaction.

Table 18: Regression coefficients: CCE and CS

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.816	.152		11.933	.000
	CCE	.661**	.054	.606	12.181	.000
Dependent Variable: CS ***. Coefficient is significant at the 1% level*						

Source: Primary data

Results in Table 18~~Table 18~~ show that customer chatbot engagement significantly predicts customer satisfaction.

4.7.3 Customer chatbot engagement and customer frustration

The study also assessed how engagement with chatbots relates to customer frustrations. A simple linear regression model was estimated, as summarised in Table 19~~Table 19~~.

Table 19: Model summary: CCE and CF

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.251[a]	.063	.059	.85588
a. Predictors: (Constant), CCE				

Source: Primary data

The R-square value of 0.063 indicates that approximately 6.3% of the variability in customer frustrations is explained by the chatbot engagement level.

Table 20: ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	12.565	1	12.565	17.153	.000[b]
	Residual	187.530	256	.733		
	Total	200.095	257			
a. Dependent Variable: CF						
b. Predictors: (Constant), CCE						

Source: Primary data

The ANOVA results in Table 20~~Table 20~~ indicate that the simple linear regression model assessing the relationship between CCE and CF is statistically valid. The highly significant F-value of 17.153 ($p < 0.001$) suggests that the regression model is meaningful and that including chatbot engagement as a predictor significantly contributes to explaining the variance in customer frustrations.

Table 21: Regression coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	4.472	.175		25.604	.000
	CCE	-.258**	.062	-.251	-4.142	.000
Dependent Variable: CF ***. Coefficient is significant at the 1% level*						

Source: Primary data

Results in Table 21~~Table 21~~ show that engagement with chatbots significantly reduces customer frustration.

4.8 Results about hypotheses.

Hypothesis 1 (H1): Perceived ease of use positively influences customer engagement.

This study hypothesised that perceived ease of use positively influences customer engagement. Regression analysis was conducted to test the hypothesis. Results in Table 15~~Table 15~~ show that perceived ease of use has a positive and significant coefficient *(B=0.480, p<.001)*. A one-unit increase in perceived ease of use is associated with a 0.480-unit increase in customer chatbot engagement, holding other variables constant. This suggests that their engagement increases as users perceive the chatbot to be easier to use. This aligns with the expectation that a user-friendly experience contributes positively to engagement. Therefore, hypothesis 1 was supported.

Hypothesis 2 (H2): Perceived performance expectancy positively influences chatbot engagement.

The study also hypothesised that performance expectancy could positively influence chatbot engagement. From the results in Table 15~~Table 15~~, performance expectancy has a positive and statistically significant coefficient (*B=0.136, p<.01*). A one-unit increase in performance expectancy corresponds to a 0.136-unit increase in customer chatbot engagement. This indicates that as users' expectations of the chatbot's performance increase, so does their engagement. Users anticipating better performance from the chatbot are likelier to engage with it. Hypothesis 2 was therefore supported in this study.

Hypothesis 3 (H3): Perceived expectant compatibility influences chatbot engagement.

Table 15~~Table 15~~ reports that compatibility has a positive and statistically significant coefficient *(B=0.168, p<.01).* A one-unit increase in compatibility is associated with a 0.168-unit increase in engagement. This implies that as compatibility increases, customer chatbot engagement also tends to increase. Users are more likely to engage with a chatbot that is perceived as compatible with their needs or preferences. Therefore, Hypothesis 3 was supported.

Hypothesis 4 (H4): Perceived social influences positively affect customer's chatbot engagement.

The study hypothesised that positive social influences positively influence customer chatbot engagement. Results from regression analysis show that social influence has a positive and statistically significant coefficient *(B= 0.268, p<.001).* A one-unit increase in social influence corresponds to a 0.268-unit increase in customer chatbot engagement. This suggests that as the influence of social factors on users' decisions to engage with the chatbot increases, so does their actual engagement. Users who feel socially influenced are more inclined to engage with the chatbot actively. Thus, there was evidence to support Hypothesis 4.

Hypothesis 5 (H5): Customer-chatbot engagement positively influences overall customer satisfaction.

The study further hypothesised that customer chatbot engagement would positively influence customer satisfaction with chatbot use. Regression results revealed that the coefficient for customer chatbot engagement is positive and statistically significant *(B=0.661, p<.001).* The positive sign implies a positive relationship: as chatbot engagement increases, customer satisfaction is also expected to increase. In practical terms, there is an average increase of 0.661 units in customer satisfaction for every one-unit increase in chatbot engagement. Hypothesis 5 was therefore supported.

Hypothesis 6 (H6): Customer-chatbot engagement influences overall customer frustration.

The study also tested the hypothesis that customer chatbot engagement would influence customer frustration. In the simple linear regression model assessing the relationship between customer chatbot engagement and customer frustrations, the coefficient for CCE is negative and statistically significant *(B= -0.258, $p < 0.001$)*. This negative coefficient implies that, on average, for every one-unit increase in chatbot engagement, customer frustrations decrease by 0.258 units. The negative sign indicates an inverse relationship: higher levels of chatbot engagement are associated with lower customer frustrations. In practical terms, the result suggests that fostering increased engagement with the chatbot may reduce customer frustrations. Hypothesis 6 was supported.

Table 22~~Table 22~~ summarises the hypotheses tested in this study.

Table 22: Hypotheses summary

Hypothesis	Description	Result
H1	Perceived ease of use positively influences customer engagement	Supported
H2	Perceived performance expectancy positively influences chatbot engagement	Supported
H3	Perceived compatibility influences chatbot engagement	Supported
H4	Perceived social influences directly affect customers' chatbot engagement	Supported
H5	Customer-chatbot engagement positively influences overall customer satisfaction.	Supported
H6	Customer-chatbot engagement quality influences overall customer frustration.	Supported

4.9 Chapter summary

This chapter presented results on analysing antecedents of customer chatbot engagement and the influence on customer satisfaction and frustration. Data cleaning was conducted, leading to a final sample of 258 respondents. Demographic profiles of the respondents were discussed, focusing on gender and age representation. Further, the research instrument was analysed for reliability and validity, ensuring that the measurement scales measured what they were intended to measure. Composite scales of the constructs were then computed and used for correlation and regression analysis to test the hypotheses formulated. Results revealed that the data supported all hypotheses. The following chapter provides a discussion of the results.

CHAPTER 5

DISCUSSION OF THE RESULTS

5.1 Introduction

This chapter discusses and explains the results in connection with the literature that were reviewed in Chapter 2 of this study. The main emphasis, therefore, lies in the discussion of the results concerning the hypotheses that were developed for this study. The study formulated and tested six hypotheses, and, as such, this chapter discusses each of these hypotheses in line with the relevant literature. A summary which encapsulates the main results is provided at the end of the chapter.

5.2 Hypothesis 1 discussion

Hypothesis 1 (H1): Perceived ease of use positively influences customer chatbot engagement.

Hypothesis 1 posits that, the perceived ease of use positively influences customer engagement, and the study's results substantiated this relationship (*B=0.480, p<.001).* The findings indicate that as users perceive the chatbot to be easier to use, there is a corresponding increase in their engagement with the chatbot. This aligns with the expectation that a user-friendly experience contributes positively to chatbot engagement.

The result not only supports Hypothesis 1 but also validates the UTAUT, as perceived ease of use is a fundamental construct in the UTAUT. The result also aligns with prior research, reinforcing the significance of perceived ease of use in influencing user attitudes and intentions toward technology adoption. Trivedi (2019) found that perceived ease of use contributes to user attitudes towards technological devices, affecting their intention to use them. Pillai and Sivathanu (2020) further corroborate this, highlighting perceived ease of use as a significant predictor of chatbot adoption intention. The results strengthen the theoretical foundation of the UTAUT model by affirming the importance of perceived ease of use in shaping users' intention to engage with chatbots.

The result that perceived ease of use significantly influences customer chatbot engagement stresses the importance for chatbot developers to prioritise user-friendly design. Ensuring that users perceive chatbots as easy to use is crucial for fostering positive engagement. Developers should address challenges related to low education levels and advanced age, which may hinder users from finding chatbots easy to use. Communicating the accessibility of chatbots for users of all ages and education levels is vital to expanding user adoption.

5.3 Hypothesis 2 discussion

Hypothesis 2 (H2): Perceived performance expectancy positively influences chatbot engagement.

Hypothesis 2 states that perceived performance expectancy positively influences chatbot engagement, and the results of this study validated this hypothesis. The analysis revealed a positive and statistically significant coefficient *($B=0.136$, $p<.01$),* indicating that as users' expectations of the chatbot's performance increase, so does their engagement. This suggests that users anticipating better performance from the chatbot are more likely to engage with it.

The results align with the extended Unified Theory of Acceptance and Use of Technology (UTAUT). This theory posits that performance expectancy significantly predicts users' intention to adopt technology. Joshi (2021) also found that performance expectancy was the most crucial factor explaining behavioural intention in the context of customer service chatbots. Users expect chatbots to provide instant responses, short answers, and efficient guidance for queries and searches. Therefore, users are more likely to engage when they perceive the chatbot as capable of superior performance, including handling complex queries effectively.

Huang et al. (2021) further highlighted the connection between user expectations and engagement. Huang et al. (2021) found that customers are more likely to trust and actively engage with a chatbot when there is a favourable sense of expected performance. In an atmosphere where users anticipate the chatbot to provide accurate answers and engage in meaningful conversations, they are more likely to devote time and effort to the interaction.

The positive relationship between perceived performance expectancy and chatbot engagement stresses the importance for organisations to invest in enhancing the capabilities of their chatbots. Ensuring that chatbots can meet user expectations for performance, efficiency, and accuracy is crucial for fostering user engagement. Communicating these capabilities to users can contribute to shaping positive performance expectations and, consequently, promoting engagement.

5.4 Hypothesis 3 discussion

Hypothesis 3 (H3): Perceived compatibility influences chatbot engagement.

Hypothesis 3 posits that perceived compatibility positively influences chatbot engagement, and the results of this study support this hypothesis. The analysis revealed a positive and statistically significant coefficient *($B=0.168$, $p<.01$),* indicating that as compatibility increases, customer chatbot engagement also tends to increase. This implies that users are likelier to engage with a chatbot perceived as compatible with their needs or preferences.

The result aligns with prior research, demonstrating that perceived compatibility positively influences chatbot engagement. Araújo and Casais (2020) identified compatibility as a critical dimension influencing users' acceptance. Similarly, Mostafa and Kasamani (2022) highlighted the importance of compatibility in building consumers' initial trust in chatbots, emphasising its impact alongside perceived ease of use and social impact. Moreover, Alt et al. (2021) reaffirmed the significance of perceived compatibility.

Therefore, the compatibility of the chatbot increases its use by customers. This aligns with the notion that users feel more confident and comfortable interacting with chatbots that are perceived as consistent with their values and lifestyle (Mostafa & Kasamani, 2022).

The result implies that developers should focus on designing chatbots that align with users' needs and preferences, ensuring a seamless integration into users' daily lives. Incorporating features that enhance compatibility, such as understanding users' buying behaviour and lifestyle, can significantly contribute to fostering positive engagement.

5.5 Hypothesis 4 discussion

Hypothesis 4 (H4): Perceived social influences positively affect customer's chatbot engagement.

The results of Hypothesis 4 revealed a positive and statistically significant coefficient *(B= 0.268, p<.001),* supporting the notion that perceived social influences positively affect customer chatbot engagement. This implies that as the influence of social factors on users' decisions to engage with the chatbot increases, their actual engagement also rises.

The result is consistent with prior research, strengthening the understanding of social influences' role in shaping user behaviour towards chatbots. Konya-Baumbach et al. (2023) found that a favourable social influence increases engagement, as customers are more likely to participate in conversations actively. This is expected since users are more inclined to engage when they feel socially influenced, perhaps seeking validation or approval from peers or other social entities.

The result is consistent with Joshi (2021), who found that social influence significantly impacts chatbot intention, with variations based on the use context. The argument is that in both personal and organisational settings, the influence of friends, family, management, or peer communities is essential in influencing the use of chatbots. Alt et al. (2021) further corroborated the result of this study, indicating that social influence has a direct and positive impact on customer engagement with chatbots, especially when users believe that the chatbot aligns with their lifestyle and social circles.

The observed positive relationship between perceived social influences and chatbot engagement in this study was expected due to the social nature of human interactions. Individuals are likely to engage more actively when they perceive that their actions are being observed or evaluated by others. Social influence, whether from peers, family, or organisational contexts, is a powerful motivator for engagement, aligning with the fundamental aspects of human behaviour and the desire for social validation.

Recognising the persuasive role of social influences, developers should consider incorporating features that leverage social factors to foster engagement. Creating chatbot interfaces that mimic positive social interactions or endorsements may contribute to increased user engagement. Additionally, organisations can strategize communication efforts highlighting positive social experiences with chatbots to influence users positively and encourage higher engagement levels. Understanding and harnessing the power of social influences can be critical in optimising the effectiveness of chatbot interactions and improving overall user satisfaction.

5.6 Hypothesis 5 discussion

***Hypothesis 5 (H5): Customer-chatbot engagement positively influences overall customer satisfaction*.**

Results of Hypothesis 5 revealed a positive and statistically significant coefficient *(B=0.661, p<.001),* substantiating the hypothesis that customer chatbot engagement positively influences overall customer satisfaction with chatbot use. As engagement with the chatbot increases, there is an expected corresponding increase in customer satisfaction. This aligns with the broader literature on customer satisfaction with chatbot interactions, as various studies indicate.

Jiang et al. (2023) found that effective interactions with chatbots contribute to higher satisfaction levels. Xie et al. (2024) demonstrated that using clever and comical language by chatbots contributes to improved customer satisfaction. In addition, Zhu et al. (2023) reaffirmed that positive engagement with chatbots contributes to increased satisfaction. The link between engaging interactions and higher customer satisfaction is also consistent with the findings of Hsu Lin (2023), emphasising improving customer satisfaction through more humanised chatbot responses. Furthermore, Xu et al. (2022) explored the influence of communication styles on customer satisfaction with chatbots and found that positive perceptions of communication styles were associated with higher satisfaction with using chatbots. It can be inferred that engaging interactions foster positive perceptions and satisfaction with use. Therefore, recognising that customer-chatbot engagement positively influences overall satisfaction highlights the importance of designing chatbots that facilitate engaging and meaningful interactions. Developers should focus on providing accurate information and creating interfaces that foster user engagement through personalised and contextually relevant interactions.

5.7 Hypothesis 6 discussion

Hypothesis 6 (H6): Customer-chatbot engagement influences overall customer frustration.

The study tested the hypothesis that customer chatbot engagement would influence customer frustration. In the simple linear regression model assessing the relationship between customer chatbot engagement and customer frustrations, the coefficient for customer chatbot engagement was negative and statistically significant *(B= -0.258, $p < 0.001$)*. The result implies that customer-chatbot engagement inversely influences overall customer frustration. Several studies in the literature provide insights that corroborate and provide context for the observed relationship. Studies by Yu-Shan Huang and Dootson (2022) and Park et al. (2021) emphasised that frustrations in customer-chatbot interactions often arise from misunderstandings, limitations in chatbot functionalities, and the chatbot's inability to resolve user issues effectively. The negative relationship observed in this study, where higher levels of engagement correspond to lower frustration levels, aligns with the idea that positive engagement mitigates misunderstandings and enhances the overall effectiveness of chatbot interactions.

Margot and Pilgrim (2020) further contributed to this understanding by highlighting that a chatbot's failure to understand and address user queries can lead to frustration. The current study suggests that effective engagement, characterised by a higher level of interaction, may alleviate frustrations associated with chatbot limitations in understanding and addressing user inquiries.

Crolic et al. (2022) found that user anger or frustration can develop during the interaction with the chatbot. Therefore, positive engagement can mitigate negative emotional reactions during interactions. Tamara et al. (2023) found that a poorly designed chatbot with inadequate features and responses might cause annoyance and frustration. As such, the argument is that effective engagement can contribute to a more satisfying experience for users, reducing frustrations arising from chatbot limitations. Engaging interactions, characterised by quick responses, personalised advice, and effective resolution of queries, contribute to a positive customer experience and diminish frustrations.

The result of this study highlights the need to focus on designing chatbots that provide accurate information and facilitate meaningful and effective interactions. By doing so, organisations can minimise customer frustrations, enhance satisfaction, and foster positive perceptions of chatbot interactions. This emphasises the strategic importance of promoting effective engagement to optimise the overall customer experience in the context of chatbot interactions.

5.8 Chapter summary

This chapter discussed the study's results on the antecedents of customer chatbot engagement and their impact on customer satisfaction and frustration.

Six hypotheses regarding the relevant literature were discussed. The results supported all the formulated hypotheses. Notably, perceived ease of use positively influenced customer engagement, aligning with prior studies emphasising the importance of user-friendly experiences. The study also found that performance expectancy and compatibility positively influenced chatbot engagement, corroborating findings from prior research on technology adoption and acceptance. Social influences were identified as significant drivers of customer engagement, reinforcing the impact of peer opinions and societal expectations on chatbot usage.

Moreover, the study established a positive association between customer-chatbot engagement and customer satisfaction, emphasising the crucial role of effective interactions in fostering user contentment. Additionally, engagement was found to inversely influence overall customer frustration, highlighting the importance of meaningful interactions in mitigating user frustrations during chatbot interactions. The following chapter concludes the study.

CHAPTER 6

CONCLUSIONS AND RECOMMENDATIONS

6.1 Introduction

This concluding chapter synthesises the study's findings and offer recommendations based on the results. Firstly, the results are integrated into research questions, and answers are provided. Recommendations will follow this, and areas of further research are provided at the end of the chapter.

6.2 Research question 1 conclusion

This study sought to identify the antecedents of customer-chatbot engagement. In exploring the antecedents of customer-chatbot engagement, this study aimed to understand what influences people to use chatbots actively. The results validated the predictions of the UTAUT model in the context of customer chatbot use. Perceived ease of use, performance expectancy, compatibility and social influence were significant predictors of customer chatbot engagement. Results suggest that when users perceive a chatbot as easy to use, expect good performance, see chatbots as compatible with their needs, and feel influenced by social factors, they are more likely to continue engaging with it. This result aligns with what previous studies have found. However, this research differs because it focuses on actual engagement rather than just the intention to use a chatbot. Unlike earlier studies that mainly examined why people try a chatbot, this study investigated what keeps them engaged once they start using chatbots.

The research substantiated that various factors, such as perceived ease of use of the chatbot, anticipated performance quality, perceived alignment with individual needs, and the influence of social dynamics, significantly contribute to the maintenance of user engagement over time. This extends the understanding beyond the initial decision to try a chatbot. Notably, this study highlighted a shift from a primary focus on adoption to a more comprehensive exploration of ongoing engagement. The study, therefore, adds depth to the existing knowledge and provides practical insights for developers and businesses**.**

Overall, this study advances the understanding of customer-chatbot engagement by confirming known antecedents within the engagement context and highlighting the shift from adoption-focused studies. The focus on engagement opens new avenues for enhanced user experiences, and provides a foundation for further exploration in this evolving field.

6.3 Research question 2 conclusion

After identifying the critical predictors of customer chatbot engagement, it was essential to analyse whether engagement with chatbots affects satisfaction with using the chatbot. The study revealed that positive engagement is associated with increased customer satisfaction. This study advanced the understanding of customer-chatbot interactions by extending the UTAUT to explore engagement's impact on satisfaction. The extension of UTAUT was necessary as this study moved beyond merely identifying the actual use antecedents to unravel the intricate dynamics of how engagement shapes user experiences. Understanding the factors that drive customer engagement and the subsequent impact on satisfaction helps companies tailor their chatbot designs to enhance the overall user experience. This goes beyond the conventional adoption-focused approach of UTAUT and aligns with the contemporary emphasis on customer-centricity.

6.4 Research question 3 conclusion

The study provided answers regarding the impact of customer chatbot engagement on customer frustrations. It was revealed that positive engagement reduces customer frustration. This study introduced a novel approach by explicitly measuring customer frustration, a facet often overlooked in previous research. This could be an essential contribution, as most studies have predominantly focused on positive outcomes, particularly user satisfaction, neglecting the equally important dimension of customer frustration. In an era where customer experience is a crucial differentiator, identifying and addressing sources of frustration is important. Isolating the impact of engagement on frustration implies that this study could equip businesses with actionable insights to refine their chatbot functionalities and mitigate potential sources of user dissatisfaction.

6.5 Recommendations

The following recommendations were made based on the results of this study.

6.5.1 User-friendly design for targeted user engagement

The results suggest a direct link between perceived ease of use and user engagement, indicating that improving the user-friendly design of the chatbot interface is paramount. To achieve optimal ease of use, business executives and development teams must prioritise the implementation of a user-centric design approach. This involves integrating human-centric design principles into the development process, ensuring the chatbot interface is not only visually appealing but also intuitive and easily navigable for users.

Chatbot developers should focus on creating a streamlined conversational flow, incorporating clear call-to-action buttons, and minimising cognitive load to enhance the overall user experience. Concentrating efforts on improving ease of use enables businesses to effectively lower the barriers to entry, fostering more comfortable and seamless interactions with the chatbot.

The practical implementation of these design principles will result in a more user-friendly interface, potentially leading to increased engagement and satisfaction among the target audience. This strategic approach acknowledges the significance of user experience in driving positive interactions, ultimately contributing to the achievement of business goals.

6.5.2 Optimising chatbot performance

The results highlighted the importance of optimising chatbot performance to surpass user expectations, necessitating a concerted effort from chatbot developers and technology experts. To achieve this, developers must integrate advanced machine learning algorithms into the chatbot's framework. These algorithms enable the chatbot to comprehensively understand user queries, respond promptly, and continually enhance its problem-solving proficiency over time.

The development cycle should incorporate regular updates and improvements, ensuring the chatbot remains at the forefront of evolving user expectations. This proactive approach not only demonstrates a commitment to technological advancement but also cultivates a perception of the chatbot as consistently high-performing. As users experience improved performance, their expectations are positively reinforced, fostering a sense of positive performance expectancy. This, in turn, contributes to sustained user engagement, as users are more likely to interact with a chatbot they perceive as reliable and proficient.

6.5.3 Improving compatibility

To enhance compatibility and foster personalised interactions, it is recommended that businesses take deliberate steps in tailoring chatbots to individual user preferences and behaviours. This requires a collaborative effort between marketing teams and developers. Firstly, marketing teams should conduct comprehensive analyses of user behaviours and preferences through data analytics and user feedback. The marketing team might have to stretch to different platforms to gather this data like social media pages and even self-proclaimed internet ombudsman like Hello Peter. This information serves as the foundation for understanding the diverse needs of the user base.

Subsequently, developers should implement customisation features within the chatbot's architecture to align its functionality with the identified user profiles. This involves integrating machine learning algorithms to adapt responses based on user history and preferences. Clear communication channels should be established between marketing and development teams to ensure seamless integration of personalised elements.

The outcome of this tailored approach is a chatbot that delivers a more personalised and relevant experience to users. Users are more likely to engage with a chatbot that understands and caters to their specific needs, thereby increasing the likelihood of positive user experiences and sustained engagement.

6.5.4 Harnessing the power of social influence

To leverage the power of social influence and enhance chatbot engagement, it is recommended that marketers and community managers undertake specific initiatives aimed at creating a positive social narrative. Firstly, marketers should strategize and implement positive marketing campaigns that highlight the benefits and positive experiences associated with chatbot usage. These campaigns can be disseminated through various channels such as social media, email newsletters, and website content.

Additionally, collaboration with influencers within the industry or relevant community can significantly impact the chatbot's social influence. Community managers should identify and reach out to influencers who align with the brand's values and target audience, fostering partnerships that authentically promote the chatbot's advantages.

Furthermore, encouraging user testimonials should be an integral part of the strategy. Actively seeking and showcasing positive experiences from users can contribute to the creation of a positive social narrative. Community managers can interact directly with users, solicit testimonials, and incorporate them into marketing materials.

The outcome of these initiatives is the establishment of a favourable social narrative surrounding chatbot usage. When users encounter positive messages from various sources, including influencers and fellow users, they are more likely to develop trust and a sense of community around the chatbot. This, in turn, contributes to increased engagement as users feel confident and motivated to actively participate in chatbot interactions.

6.5.5 Improving overall satisfaction

To enhance customer satisfaction and alleviate frustration, businesses should implement proactive engagement strategies within chatbots. Developers play a key role in integrating features such as personalised recommendations, timely notifications, and proactive issue resolution. This involves incorporating machine learning algorithms to analyse user behaviour and preferences, allowing the chatbot to anticipate and address user needs in real-time. Timely notifications can be implemented through push notifications or in-chat alerts to keep users informed about relevant updates or personalised recommendations.

Furthermore, establishing a robust monitoring system is crucial for developers and quality assurance teams. Regularly updating chatbot functionalities based on user feedback and evolving customer needs is imperative. This requires the implementation of feedback loops, sentiment analysis, and issue-tracking mechanisms. Proactive identification and resolution of potential sources of frustration contribute to a smoother user experience.

The outcome of these strategies is enhanced overall customer satisfaction. Users benefit from personalised interactions, timely notifications, and effective issue resolution, leading to a positive and satisfying experience. Additionally, the proactive approach to identifying and addressing potential sources of frustration reduces user dissatisfaction and reinforces confidence in the chatbot's reliability and effectiveness.

6.6 Suggestions for further research

Future research could explore the influence of cultural factors on customer chatbot engagement. Given the global use of chatbots, understanding how cultural nuances shape user expectations, preferences, and engagement patterns would be valuable. Researchers can investigate whether the customisation of chatbots based on cultural differences enhances engagement and satisfaction. This study could contribute to developing culturally adaptive chatbots, providing insights into tailoring conversational agents to diverse user backgrounds.

Another avenue for further research involves examining the longitudinal impact of chatbot engagement on customer brand loyalty specifically in South African organisations. While this study focused on immediate satisfaction and frustration, future research could explore how sustained positive engagement with chatbots influences long-term customer loyalty. This could involve longitudinal studies tracking users over an extended period to understand the enduring effects of chatbot interactions on brand perception, trust, and loyalty.

As chatbots become more sophisticated in influencing user behaviour, exploring the ethical dimensions of persuasive chatbot design becomes crucial. Future research could investigate the boundaries of persuasive strategies employed by chatbots and their impact on user decision-making. This includes examining the potential for unintended consequences, such as manipulation or loss of user autonomy. Ethical considerations surrounding data privacy, consent, and the responsible use of persuasive techniques in chatbot interactions could be valuable areas for in-depth exploration.

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APPENDIX A: RESPONDENT AGREEMENT FORM

Dear Respondents,

You are invited to participate in an academic research study conducted by Lesego J M Raphela for a qualification in Masters of Management in Digital Business from the University of Witwatersrand Business School.

The study aims to investigate the influence of chatbots on customer experience and frustrations in self-help functions across South Africa.

This survey is **conducted** anonymously; hence, your name or directly identifiable information will not be requested. Your responses will be handled with extreme **confidentiality** because they cannot be used to identify you personally.

▪ Your participation in this study is very important to us. However, there are no negative effects if you decide not to participate or if you decide to stop at any point.

▪ Please select an answer that applies from the option provided. Please respond as honestly as possible about your experience.

The survey should not take more than **15** minutes of your time.

▪ The study results will be used for academic purposes only and may be published in an academic journal.

Please indicate your acceptance or refusal to complete the survey by ticking the options below.

- I agree to continue with the survey.
- No, I do not agree to continue with the survey.

APPENDIX B: RESEARCH INSTRUMENT

Questions					
Interaction Experience Question					
Have you used a chatbot for self-help before?	Yes	No			
Demographic Information					
Gender	Male	Female	Other	I prefer not to say	
Age	18-24	25-34	35-44	45-54	55 or above
How frequently do you use self-help functions (e.g., FAQs, knowledge base, tutorials)?	Never	Rarely	Occasionally	Frequently	Very frequently
	1=Strongly Disagree	2=Disagree	3 Neither Agree or Disagree	4=Agree	5=Strongly Agree
Compatibility					
The chatbot's responses were compatible with my needs.					
The chatbot's interface was compatible with my device(s).					
The chatbot's language and tone were compatible with my preferences.					
The chatbot services are compatible with my values.					
Perceived ease of use					
I find it easy to interact with chatbots.					
I find chatbots easy to use					
The chatbot's interface is user-friendly.					

Learning to operate chatbots was easy for me.					
Performance expectancy					
The chatbot provided accurate and relevant information.					
The chatbot effectively resolved my queries or issues.					
Using the chatbot enabled me to accomplish the self-help process quickly.					
The chatbot improved my overall self-help experience.					
Social influence					
My friends and family value the use of chatbots.					
I believe that others (e.g., friends and colleagues) think using chatbots is a good idea.					
The people who influence me use chatbots.					
I am influenced by others' positive opinions about using the chatbot.					
The people's recommendations or suggestions influenced my decisions.					
Customer Experience					
The overall customer experience when using a chatbot as self-service tool is satisfactory					
The response time of a chatbot when using it as self-service tool is quick.					
The information provided by chatbots when using them as self-service tools is accurate.					
The personalisation and tailored recommendations provided by chatbots as self-service tools are helpful.					
Chatbots as self-service tools are user-friendly and easy to navigate.					

Customer Frustrations					
Getting complex queries or issues resolved through chatbots as self-service tools is challenging.					
Chatbots lack human-like conversation or empathy, which can be frustrating.					
Long wait times for responses from chatbots are frustrating.					
I will likely abandon using a chatbot and seek assistance from a human representative when experiencing frustrations or challenges.					
Customer-Chatbot Engagement Quality					
I encourage friends and relatives to do business with a chatbot seller.					
I consider a seller using chatbots my first choice when buying products.					
In your opinion, how does using a chatbot for self-help functions affect your overall customer experience?	1=Negatively	2=No effect	3=Positively		
Would you recommend using a chatbot for self-help functions to others?	Yes	No			

APPENDIX C: RESULTS

Reliability Measurement per construct.

PEOU

Reliability Statistics

Cronbach's Alpha	N of Items
.858	4

PE

Reliability Statistics

Cronbach's Alpha	N of Items
.940	4

CO

Reliability Statistics

Cronbach's Alpha	N of Items
.756	4

SI

Reliability Statistics

Cronbach's Alpha	N of Items
.818	5

CCE

Reliability Statistics

Cronbach's Alpha	N of Items
.515	4

CX

Reliability Statistics

Cronbach's Alpha	N of Items
.850	5

CF

Reliability Statistics

Cronbach's Alpha	N of Items
.661	4

Item Statistics

	Mean	Std. Deviation	N
How frequently do you use self-help functions (e.g., FAQs, knowledge base, tutorials)?	2.98	.996	258
The chatbot's responses were compatible with my needs	3.48	1.081	258
The chatbot's interface is compatible with my device(s).	4.13	1.065	258
The chatbot's language and tone are compatible with my preferences	3.93	.982	258
The chatbot services are compatible with my values	3.66	.921	258
I find it easy to interact with chatbots	3.73	1.198	258

I find chatbots easy to use	3.95	1.123	258
The chatbot's interface is user-friendly	3.86	1.096	258
Learning to operate chatbots was easy for me	4.21	1.049	258
The chatbot provided accurate and relevant information	3.36	1.162	258
The chatbot effectively resolved my queries or issues	3.16	1.227	258
Using the chatbot enabled me to accomplish the self-help process quickly	3.43	1.290	258
The chatbot improved my overall self-help experience	3.38	1.306	258
My friends and family value the use of chatbots	2.87	1.015	258
I believe that others (e.g., friends and colleagues) think using chatbots is a good idea	3.30	1.062	258
The people that influence me use chatbots	3.10	1.068	258
Others influence my favourable opinions about using chatbots	3.08	1.204	258
The people’s recommendations or suggestions influenced my decisions	2.97	1.231	258
The overall customer experience when using a chatbot as self-service tool is satisfactory	3.40	1.219	258
The response time of a chatbot when using it as self-service tool is quick.	4.17	1.061	258
The information provided by chatbots when using them as self-service tools is accurate	3.38	1.168	258
The personalisation and tailored recommendations provided by chatbots as self-service tools are helpful	3.37	1.157	258

Chatbots as self-service tools are user-friendly and easy to navigate	3.83	1.086	258
It is challenging to get complex queries or issues resolved through chatbots as self-service tools	4.07	1.209	258
Chatbots lack human-like conversation or empathy, which can be frustrating	3.82	1.171	258
Long wait times for responses from chatbots are frustrating	3.18	1.397	258
I am likely to abandon the use of a chatbot and seek assistance from a human representative when experiencing frustrations or challenges	4.07	1.261	258
I encourage friends and family to do business with a seller who uses a chatbot	3.09	1.113	258
I consider a seller who uses chatbots to be my first choice when buying products	2.63	1.174	258
In your opinion, how does using a chatbot for self-help functions affect your overall customer experience?	2.29	.772	258
Would you recommend using a chatbot for self-help functions to others?	1.26	.437	258