Factors affecting the adoption of chatbots in the South African financial services context

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ABSTRACT

This research focuses on the factors that affect the adoption of chatbots in the South African financial services industry. It explores the direct and indirect influences of the constructs of the Unified Theory of Acceptance and Use of Technology (UTAUT), the attitude construct from Technology Acceptance Model (TAM), self-efficacy, as well as security-related construct.

The study used a cross-sectional, quantitative research methodology, and data was collected through self-administered online questionnaires. Data analysis included correlation and regression analysis, factor reduction, exploratory factor analysis, mediation, and moderation analysis. The research constructs were tested for direct and indirect effects, additionally, gender, age, and previous chatbot experience was used to moderate the behavioural intention relationships in the conceptual framework.

The findings indicate that facilitating conditions, attitude, perceived risk, effort expectancy, utilitarian performance expectancy, perceived security, perceived trust, SI, and hedonic performance expectancy have an indirect or direct effect on chatbot adoption in South Africa. However, self-efficacy proved to be an insignificant construct in the research model.

In the wake of the digital revolution, the current state of chatbot usage in South Africa seems to be growing with more service providers already having implemented chatbots into their businesses.

KEYWORDS: chatbot, technology adoption, financial services

DECLARATION

I, Seolebaleng Priscilla Kedijang, student number 453509, hereby declare that this Masters thesis is my own work except where indicated in the references and acknowledgements. I hereby declare that I have properly acknowledged and referenced all sources of information used in this study. This research was conducted at Wits Business School (WBS) under the supervision of Dr Chiedza Ndlovu. It is submitted in partial fulfilment of the requirements for the degree of Master of Management in Digital Business at the University of the Witwatersrand, Johannesburg. It has not been submitted for examination or any degree in any other university.

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Signed on Friday 30 June 2023

DEDICATION

TO GOD, RAMASEDI O MPONISETSANG TSELA.

TO MY PARENTS, IPELENG KEDIJANG AND KEABOKA KEDIJANG.

TO MY BROTHERS, TLOTLO KEDIJANG AND TLHAGO KEDIJANG.

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To all my friends, cousins, and relatives, you all gave me assistance and support in different ways, thank you.

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ATT – Attitude

CI – Confidence Interval

DV – Dependent Variable

EE- Effort Expectancy

FC – Facilitating Conditions

HBR – Harvard Business Review

HPE – Hedonic Performance Expectancy

IV – Independent Variable

PE – Performance Expectancy

PR – Perceived Risk

PS – Perceived Security

PT - Perceived Trust

SD - Standard Deviation

SE – Self-Efficacy

SI – Social Influence

TAM – Technology Acceptance Model

UPE – Utilitarian Performance Expectancy

UTAUT – Unified Theory of Acceptance & Use of Technology

1 CHAPTER 1. INTRODUCTION

The statement of purpose, background, research problem and research objectives will be the first subsections provided in this chapter. These will set the context for this research report. The following subsections in this chapter will be the rationale for this research, delimitations of this research, the definition of terms and a list of assumptions about this research. The final subsection will provide a brief chapter outline of the rest of this research report.

1.1 STATEMENT OF PURPOSE

This quantitative study explored the factors that affect the adoption of chatbots in the South African financial services industry in the context of individuals.

Below is a diagrammatic representation of the conceptual framework which underpinned this research. It is a combination of the Unified Theory of Acceptance and Use of Technology (UTAUT), the attitude (ATT) construct from the Technology Acceptance Model (TAM), self-efficacy (SE), and security-related constructs – perceived risk (PR), perceived security (PS), and perceived trust (PT) - applied by Khalilzadeh, Ozturk and Bilgihan (2017).

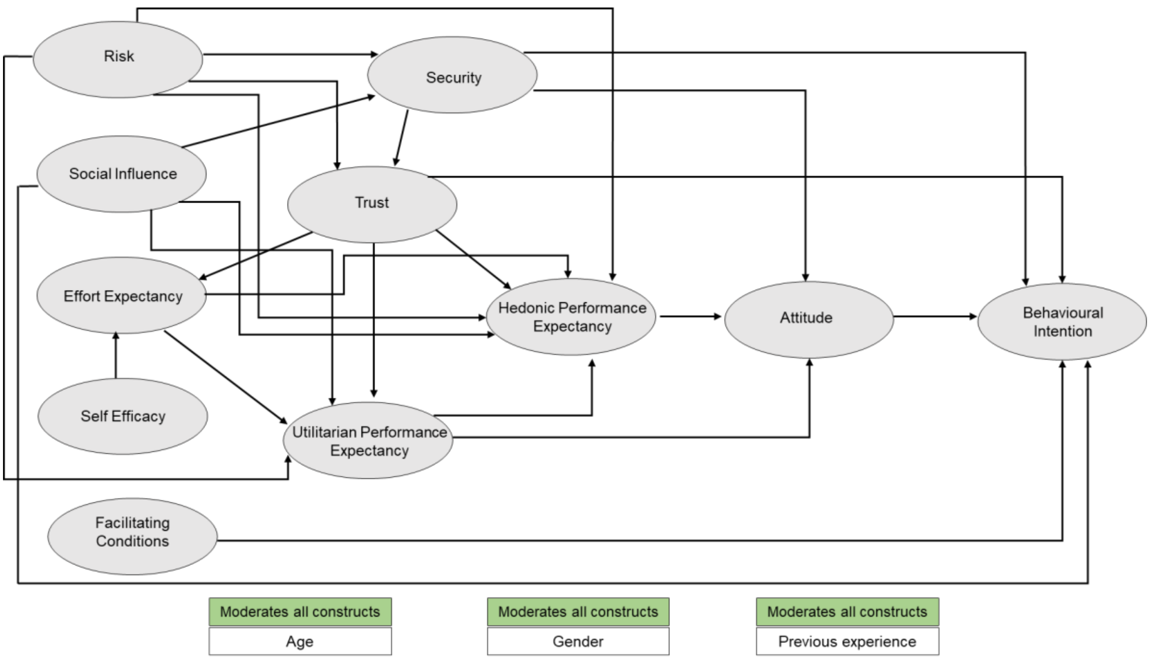


Figure 1: Conceptual framework for this study (Khalilzadeh, Ozturk and Bilgihan, 2017)

Although the UTAUT model considers user behaviour and behavioural intention (BI) as two separate constructs, this study adopted BI as a proxy for user behaviour. This conceptual framework uses age, gender, and previous chatbot experience as moderating factors.

Khalilzadeh, Ozturk and Bilgihan (2017) proved that the above conceptual framework provides better explanatory power and predictive accuracy of BI to adopt and accept technology, than the original UTAUT model.

ATT towards technology and SE are not direct determinants of BI in the UTAUT model, but this study extended UTAUT by including the ATT and SE constructs from TAM, and security-related constructs as demonstrated above.

1.2 BACKGROUND OF THE STUDY

The digital age has brought about immense pressure on businesses to continuously innovate their business models (Verhoef, Broekhuizen, Bart, Bhattacharya, Dong, Fabian & Haenlein, 2019). Digitalisation in the financial services industry has fundamentally changed how customers interact with service providers (Accenture, 2017). Faced with rapid digital disruptions, financial service providers worldwide are constantly looking for innovative ways to keep up with technology, improve customer services and keep operational costs low (Accenture, 2018).

An area of growing interest is in the application of AI technologies, using conversational techniques and creating AI-based chatbots (HBR, 2018). Businesses are deploying chatbots to automate customer service (Sheehan, Jin & Gottlieb, 2020). And more recently, the launch of ChatGPT, Google Bard and Bing Chat has seen millions of people adopting the use of these conversational agents. Chatbots are intelligent agents with the ability to respond to an individual's request intelligently, learn the individual's preferences and behaviour and engage in conversation (Ling, Tussyadiah, Tuomi, Steinmetz & Ioannou, 2021).

The roots of conversational chatbots lie in MIT's Professor Joseph Weizenbaum's work, who created the first chatbot in 1964 and called it Eliza (Weizenbaum, 1966). This chatbot facilitated interaction between humans and a machine through text-based communication and it followed mathematician, Alan Turing's *viva voce*, a one-to-one direct questioning test that examines machine thinking (Turing, 1950; Weizenbaum, 1966). Alan Turing's questioning test claimed that chatbots can exhibit intelligent, human-like responses, but also have limitations as there are times it could produce incorrect responses (Turing, 1950). Several years later, Turing's test is still applicable and chatbots still follow this question-answer method. The natural use case for chatbots is frequently asked questions (FAQs) – answering common questions from customers within a brief conversation (Accenture, 2018). By answering common questions, chatbots learn and adapt to customer preferences, and can anticipate future customer needs (HBR, 2020).

As the recent COVID-19 pandemic has forced some aspects of our everyday lives online, the pressure on businesses to meet customer expectations is high (HBR, 2020). Now more than ever, customers expect seamless engagements that are convenient and valuable, and demand personalised interactions with businesses (HBR, 2020). Organisations can benefit from using chatbots to provide better user support (HBR, 2020).

According to research by Accenture (2018), Chief Information Officers and Chief Technology Officers around the world believe that chatbots will play a critical role in business operations in future, with 56% asserting that chatbots are driving digital disruptions in their industries. Business executives believe that chatbots will enable personalised attention to clients and bring greater value to the customer's overall experience (Accenture, 2018).

Chatbots drive seamless and effortless customer experiences and the usage of chatbots is bound to increase (Gartner, 2020). Advancements in artificial intelligence, natural language processing and voice recognition technology have led to increased availability and use of conversational agents such as chatbots (Ling et al., 2021). Gartner (2020) predicted that 70% of customer interactions will involve an emerging technology such as artificial intelligence, machine learning applications, or chatbots by 2022.

Chatbots are gradually becoming a common solution for businesses to provide customer services (Ling et al., 2021). According to a Forbes Insights survey of 700 senior executives, 86% of companies that are adopting AI technologies are using chatbots for customer service (Alger, 2018). It is becoming important for businesses to consider if chatbots have the sophistication to meet customer needs (Alger, 2018). Executives believe that chatbots can provide better customer support, and help to meet customer expectations (HBR, 2020).

When implemented effectively, chatbots can improve customer service, reduce operational costs, and improve responsiveness to customer requests (News24, 2022). In the banking industry, for example, the effective implementation of chatbots can bring about several advantages. A recent Forbes publication indicated that some of the advantages of using chatbots in the banking industry include the ability to monitor transactions and therefore minimise fraud risk, the ability to analyse customer data and documents ahead of loan origination and provide personalised wealth management and investment recommendations (Marr, 2023).

As the implementation of chatbots in businesses becomes popular, understanding the drivers of individual acceptance is also becoming critical (Ling et al., 2021). Organisations must understand customer needs before implementing chatbot technology as a solution (Alger, 2018). And more importantly, the reasons why customers use chatbots.

One of the challenges individuals face when interacting with a financial services provider is long waiting periods and slow turnaround times. This is a challenge that chatbots can address. Chatbots help customers by understanding what they are looking to achieve, and either giving them the information or guiding them in the right direction (Monzon, 2021). Chatbots have the advantage of not having a language barrier, operating 24 hours, as well as lower operational costs in comparison to human customer service centres (Jang, Jung & Kim, 2021).

1.3 RESEARCH PROBLEM

Chatbot adoption is an emerging subject of interest, for instance, Lubbe and Ngoma (2021) studied the adoption of chatbots amongst the South African youth population by applying TAM and extending it with three constructs; perceived ease of use and perceived usefulness as developed by Davis (1989) and perceived playfulness as added by Moon and Kim (2001). Pillai and Sivathanu (2020) investigated the BI to use chatbots in the hospitality industry in India by applying TAM and extending it, including technology anxiety, PT, and perceived intelligence as additional constructs.

Given the increasing popularity of chatbots, academic research is actively being conducted on this technology (Jang, Jung & Kim, 2021). Some studies have focused on the technical aspects of chatbots such as the technical architecture and algorithms used in chatbots (Chakrabarti & Luger, 2015), while other studies have looked at customer satisfaction aspects related to the usage of chatbots (Chung, Ko, Joung & Kim, 2020), and some have assessed the factors that influence the adoption of chatbots in various contexts (Ling et al., 2021; Pillai & Sivathanu, 2020; Lubbe & Ngoma, 2021).

Current literature indicates that individuals want convenience, flexibility and quick turnaround times when interacting with chatbots (Djelassi, Diallo & Zielke, 2018). With Gartner (2020) having predicted that 70% of customer interactions will be via a chatbot by the end of 2022, this growing interest in chatbot technology warrants researchers to explore the factors underlying the adoption of this technology in different industries and geographical locations.

Most studies have focused on developed markets wherein chatbots are well established, such as France (Djelassi, Diallo & Zielke, 2018), Australia (Wang, Harris & Patterson, 2013), the United States (Lee & Lyu, 2016), China (Yang, Lu & Chau, 2013), and India (Pillai & Sivathanu, 2020) for example, with only a few focusing on developing markets (Lubbe & Ngoma, 2021). Hence, this study chose to address this problem and contribute to the limited literATT towards usingre on chatbot adoption in a developing market context, specifically, South Africa.

This research aimed to contribute to the existing knowledge on chatbot adoption in a developing market by integrating and applying the constructs from the UTAUT and TAM frameworks, and security related, specifically in the financial services industry.

1.4 RESEARCH OBJECTIVES

The main intention of this research was to determine the factors affecting the adoption of chatbots in the South African financial services industry.

In achieving this research objective, the UTAUT, and the SE and ATT constructs from TAM, as well as security-related constructs – PR, PS, and PT were combined to support this research, and a quantitative research design was adopted. Quantitative research was selected because it is suitable in instances where the research must identify factors that influence a certain outcome, and where the research aims to gain an understanding of the best predictors of that outcome, and thus a quantitative approach was appropriate for this study Creswell and Creswell (2018).

The intention of this study, therefore, resulted in the following research objectives:

i. To investigate whether the UTAUT and TAM framework constructs - facilitating conditions (FC), attitude (ATT), perceived risk (PR), effort expectancy (EE), utilitarian performance expectancy (UPE), perceived security (PS), self-efficacy (SE), perceived trust (PT), social influence (SI), and hedonic performance expectancy (HPE) - are factors that directly or indirectly affect the adoption of chatbots in the South African financial services industry.

ii. To assess if the aforementioned factors directly or indirectly affect an individual's BI to adopt and use chatbots in the South African financial services industry.

iii. To ascertain if there is any evidence that age, gender, and previous chatbot experience moderate the BI to adopt chatbots in the South African financial services industry.

1.5 RATIONALE

Jang, Jung and Kim (2021) indicated that Korean businesses have realised the potential of using chatbots to fulfil customer queries and plan to deploy them soon. More specifically, financial services providers are actively adopting chatbots in their digital transformation efforts in the Korean market (Jang, Jung & Kim, 2021). South Africa is no exception to the observation made by Jang, Jung and Kim (2021).

The growing use of technology by South African businesses has seen a rise in the use and implementation of chatbots (Gavaza, 2022). According to a Business Day publication, chatbots have gained popularity in South African client-facing businesses to increase efficiency by cutting operational costs and increasing productivity (Gavaza, 2022). Specifically in the financial services industry, for instance, CompariSure, a South African fintech company distributes financial services products through a chatbot platform used in messaging applications such as Facebook Messenger and WhatsApp (Gavaza, 2022). Another example is Nedbank, one of the leading banks in South Africa, which introduced Enbi in 2021 – a chatbot assistant available to its customers at any time of day (Monzon, 2021). And more recently, the Moola chatbot by Capitec Bank was launched recently and interacts with customers' money-related related matters and topics (IT Web, 2023).

The primary question for financial services providers is, what drives individuals to have the BI to use chatbots? In today's business environment, understanding customer needs and enhancing their experience is the key to a competitive advantage (Li, Wang, Wang & Zhou, 2019). Technology adoption models provide a useful tool for businesses to assess the likelihood of success of new technology introductions (Venkatesh, Morris, Davis, & Davis, 2003). Discovering and analysing the factors that influence the adoption of chatbots is becoming more important as we see more businesses turn to chatbots as a business solution (Ling et al., 2021).

Firstly, from a theoretical perspective, an improved understanding of an individual's ATT towards the adoption and use of a novel technology allows the evaluation and application of current frameworks (Ling et al., 2021). In so doing, researchers can identify if there is a need to refine the current frameworks, or whether to introduce new frameworks and models (Ling et al., 2021).

And secondly, understanding the factors that influence the adoption of chatbots will provide businesses with insight to know the drivers of the adoption and use of chatbots (Ling et al., 2021). Knowing the factors that influence individuals to adopt technology can help businesses improve the technology functionality and operational features, and in turn, improve customer experience and loyalty (Li, Wang, Wang & Zhou, 2019).

This study will provide valuable practical implications for financial services providers by explaining why individuals adopt and use chatbots.

To conduct this research, this study adopted the UTAUT model and extended it by incorporating the SE and ATT constructs from TAM, as well as security-related constructs (i.e., PR, PS, and trust) applied by Khalilzadeh, Ozturk and Bilgihan (2017) in their study to ascertain factors that drive individuals to adopt near-field communication mobile payment. This framework was most suitable for this study as it was confirmed to offer improved explanatory power and predictive accuracy (Khalilzadeh, Ozturk & Bilgihan, 2017).

1.6 DELIMITATIONS

This section outlines the delimitations of this research. The sample, conceptual, theoretical and research methodology delimitations have been provided below, and these have narrowed the scope and boundaries of this study.

SAMPLE AND POPULATION DELIMITATIONS

i. This study focused only on the perspective of individuals and did not consider organisational factors.

GEOGRAPHICAL, INDUSTRY AND TECHNOLOGY DELIMITATIONS

i. This research focused specifically on the South African financial services industry and did not include other geographical regions or industries.
ii. Only the factors affecting the adoption of chatbots were considered for this study, and this research did not include factors affecting the adoption of any other digital technology.

CONCEPTUAL DELIMITATIONS

i. The conceptual framework applied in this study consists only of the constructs of UTAUT (FC, PE, EE, SI), SE and ATT constructs from TAM and security-related constructs (i.e., PR, PS, and PT), and no other constructs from other frameworks.

THEORETICAL DELIMITATIONS

i. This study was delimited to theories and concepts that relate only to the UTAUT and TAM frameworks and did not include other theoretical frameworks.

RESEARCH METHODOLOGY DELIMITATIONS

i. This study adopted a quantitative research methodology using an online survey and did not consider any qualitative research methods such as interviews.
ii. The data collection for this research was cross-sectional in nature and therefore the results only reflect a point in time and do not include historical or future trends related to the adoption of chatbots in the South African financial services industry.

1.7 DEFINITION OF TERMS

The following definitions are pertinent in providing context to this study.

Adoption: The process of an individual accepting and integrating new technology into their everyday lives.

Chatbot: A disembodied conversational agent that holds a natural language conversation via a text-based environment to engage the user in either a general-purpose or task-oriented conversation (Chaves & Gerosa, 2021). Text-based chatbots are designed to converse and interact with users through natural, written language.

Factor(s): Refers to an element or component that contributes to a certain result.

Financial services: This segment of the economy is made up of a variety of financial firms including banks, investment houses, lenders, finance companies, real estate brokers, and insurance companies.

1.8 ASSUMPTIONS

This study made the following assumptions:

- **Assumption 1:** Individuals use chatbots when interacting with South African financial services providers.

- **Assumption 2:** Individuals who interact with South African financial services providers have some level of experience and familiarity with chatbots in general.

- **Assumption 3:** The adoption of chatbots, from an individual's perspective, in the South African financial services industry may be influenced by FC, ATT, PR, EE, UPE, PS, SE, PT, SI, and HPE.

- **Assumption 4:** The adoption of chatbots in the South African financial services industry may vary based on an individual's age, gender, and previous experience with chatbots.

The above-mentioned assumptions are reasonable and are aligned with previous studies (Shin, 2009; Mohammadi, 2015; Blut, Wang & Schoefer, 2016; Khalilzadeh, Ozturk & Bilgihan, 2017). These assumptions are fundamental to this study and form the basis of this research. As such, ignoring these assumptions would affect the research outcome and possibly lead to inaccurate findings.

1.9 CHAPTER OUTLINE

The main purpose of this research was to determine the factors affecting the adoption of chatbots in the South African financial services industry.

This report begins by reviewing scholarly articles relevant to technology adoption theories and concepts and outlining the research hypotheses in Chapter 2. The research methodology to address the hypotheses that arose from the literature review is then detailed in Chapter 3, following which, Chapter 4 presents the results of the research, hypothesis by hypothesis. Chapter 5 synthesizes the research results with the scholarly articles provided in the literature review. To conclude this report, Chapter 6 integrates the research results with the research objectives of this study, and provides recommendations based on the research.

2 CHAPTER 2. LITERATURE REVIEW

2.1 INTRODUCTION

The objective of this chapter is to review the literature on technology adoption. The key concepts of this study will be highlighted in the background discussion, followed by the literature review of the conceptual framework together with the hypotheses of this study. The next section will describe the theoretical and conceptual framework of this study, as well as provide a synthesis which supports the conceptual framework applied in this research. The chapter will conclude by restating the hypotheses developed throughout the chapter.

To conduct this literature review, databases such as JSTOR, EbscoHost, Science Direct and the University of Witwatersrand e-library were searched for related studies. The main keywords used in the search criteria included “unified theory of acceptance and use of technology”, “technology acceptance model”, “chatbot technology acceptance”, and “chatbots”. The search was mainly focused on publications during 2003 – 2023 so that the literature review can focus on periods when chatbots started gaining popularity amongst the public (Rapp, Curti & Boldi, 2021). Scholarly articles published outside this date range were considered if they were seminal and influential.

2.2 BACKGROUND DISCUSSION

2.2.1 CHATBOTS

A chatbot is an automated technology which individuals can interact with using voice or text, and instruct it to access information, complete tasks or execute transactions (Accenture, 2018). Chatbots enable engagement via messaging, text, or speech (Insider Intelligence, 2022). A chatbot gathers information about what the customer is asking and helps to manage the customer’s query quickly and efficiently (Nedbank, 2022).

Ling et al. (2021) made the distinction between text-based chatbots and voice-based chatbots. The chatbot ecosystem includes voice-based chatbots such as Siri, Alexa, and Google Home, and text-based chatbots that are deployed to instant messaging platforms (Sheehan, Jin & Gottlieb, 2020). The context used in this research was text-based chatbots which will henceforth be referred to as chatbots.

Chatbots sustain interaction with humans through text-based inputs and outputs and are commonly integrated into messaging applications such as WhatsApp and Facebook, or on websites (Ling et al., 2021). Chatbots are best reserved for scripted interactions with individuals (Alger, 2018). For chatbots to have the highest possible chance of adoption, the experience that they provide to individuals should be as close as possible to interacting with a human (Nedbank, 2022).

2.2.2 UTAUT, TAM AND SECURITY-RELATED CONSTRUCTS

According to Kajol, Singh and Paul (2022), UTAUT is one of the most applied technology acceptance frameworks in research. Venkatesh et al. (2003) developed the UTAUT model by synchronising aspects of eight behavioural theories previously applied in technology acceptance studies.

These models are – the Technology Acceptance Model (TAM), the Theory of Reasoned Action (TRA), the Motivational Model (MM), the Theory of Planned Behaviour (TPB), the Model of Personal Computer Utilization (MPCU), Innovation Diffusion Theory (IDT), the Combined TAM and TPB model (C-TAM-TPB), and models which reflect Social Cognition Theory (SCT). The UTAUT outdid these models using the same data set and better explained the variance in BI to adopt technology (Venkatesh et al.¸ 2003).

The UTAUT theorizes that four constructs – PE, EE, SI, and FC – play a significant role as direct determinants of BI and use behaviour (Venkatesh, et al., 2003). Since this study is extending the UTAUT, the ATT construct from TAM is theorized to be a direct determinant of BI. TAM is based on the premise that ATT is the main mediator between the model constructs and BI (Davis, 1989; Davis, Bagozzi & Warshaw, 1989; Khalilzadeh, Ozturk & Bilgihan, 2017).

The SE construct will also be applied in this study. SE finds its roots in SCT by Compeau and Higgins (1995) and was evaluated in the formulation of the UTAUT. Although it was found to not be a direct determinant of BI in the UTAUT, the construct will be considered in this study.

The PE construct from the UTAUT was split into two dimensions by Yang (2010) and therefore, making the distinction between HPE and UPE. Yang (2010) made this distinction because the PE construct from UTAUT measures utilitarian benefits only, and neglects to consider hedonic elements. The conceptual framework in this study also considered UPE and HPE as two separate constructs.

In the wake of privacy-related concerns with technology, the addition of PR, PS and PT became critical additional variables to this study (Khalilzadeh, Ozturk & Bilgihan, 2017). And finally, the moderating role of age, gender, and previous experience is also considered in this research.

Following this, the next section of this chapter provides the literature review for the key concepts outlined above which will be applied in this study – FC, ATT, PR, EE, UPE, PS, SE, SI, HPE, BI, and the moderators of age, gender, and previous experience.

2.3 FACTORS AFFECTING THE ADOPTION OF TECHNOLOGY

This section will review literature related to the factors that affect the adoption of technology and develop the hypotheses to address research objective (i).

2.3.1 FC

The degree to which one believes that organizational, structural, administrative, and technical infrastructure exists to facilitate the application and use of technology represents the FC construct in UTAUT. (Venkatesh et al., 2003). Wong, Tan, Lee, Ooi and Sohal (2020) recently extended this definition by stating that FC could also include resources such as the technical competencies required to use technology. FC are aspects that remove the barriers to use using technology, but instead, provide individuals with support to easily use technology (Venkatesh et al., 2003).

The FC of technology are positively correlated with the use of that technology (Venkatesh et al., 2003; Im, Hong & Kang, 2011). This means that, if there are more FC that support the use of technology, then individuals would be more likely to adopt that technology (Im, Hong & Kang, 2011). Baptista and Oliveira (2015) supported this view by stating that an individual who has access to a set of favourable FC associated with technology will have a greater BI to use it.

Certain measurement items have been applied in previous studies to test the FC construct in the UTAUT model. These include, whether individuals have the necessary resources to use technology, the necessary knowledge pertaining to the technology, whether the technology is easy to use, the compatibility of the technology with other technologies used by the individual, any guidance available to individuals on how to use the technology, and if there are instructions to facilitate the use of the technology (Moore & Benbasat, 1991; Taylor & Todd, 1995; Venkatesh et al., 2003).

Wong et al. (2020) indicated that when individuals have the right FC, technology adoption is more likely. Ling et al. (2021) also emphasised the importance of FC; indicating that FC play an important role in the BI to use technology.

Lu, Cai and Gursoy (2019) found that FC positively affected BI to use chatbots. In the UTAUT model, FC have a direct positive relationship with use behaviour, but no effect on BI (Venkatesh et al., 2003). However, since this study adopted BI as a proxy for use behaviour, a direct positive relationship is hypothesised between FC and BI (Khalilzadeh, Ozturk & Bilgihan, 2017).

1.1. Hypothesis 1

Based on the above arguments, the following hypothesis is positioned:

H1: The FC for using chatbots in the South African financial services industry positively affects BI to use chatbots.

2.3.2 ATT

ATT refers to the positive or negative feelings individuals have when using technology (Li, Wang, Wang & Zhou, 2019). The relationship between ATT and BI represented by TAM denotes that individuals form the intention to perform a certain behaviour if they have a positive ATT towards that behaviour (Davis, 1989). In fact, in the main predecessors of UTAUT (TRA, TAM and TPB) ATT is the main determinant of BI to use technology (Khalilzadeh, Ozturk & Bilgihan, 2017).

Dwivedi, Rana, Jeyaraj, Clement and Williams (2019) found that ATT played a significant role in determining the acceptance of technology, and that ATT had a direct positive effect on BI to adopt technology.

1.2. Hypothesis 2

H2a: HPE from using chatbots in the South African financial services industry positively mediates the effect of EE on ATT towards using chatbots.

H2b: UPE from using chatbots in the South African financial services industry positively mediates the effect of EE on ATT towards using chatbots.

H2c: ATT towards using chatbots in the South African financial services industry positively mediates the relationship between HPE and BI to use chatbots.

H2d: ATT towards using chatbots in the South African financial services industry positively mediates the relationship between UPE and BI to use chatbots.

2.3.3 PR

There is a perceived sense of risk concerning disclosure of personal and financial information when interacting with technologies (Tan & Teo, 2000). PR is a broad term which includes various types of risks such as financial risk, performance risk, psychological risk, social risk, and privacy risk affecting the adoption of technology (Kajol, Singh & Paul, 2022). This construct is often viewed as a multidimensional construct which Pavlou (2003) defined as an individual's subjective belief of suffering a loss in pursuit of a desired outcome.

For this research however, only two dimensions of PR were studied – performance risk and privacy risk. According to Chiu, Wang, Fang and Huang (2014), performance risk refers to the probability that technology may fail to function as expected, and privacy risk is the potential loss of control over one's personal information. Individuals perceive risk when they are faced with uncertainty and potentially undesirable consequences resulting from using technology (Taylor, 1974). The perception and presence of risk is pivotal in understanding BI and technology adoption theories as it might produce anxiety or ambiguity (Taylor, 1974).

With the rapid penetration of internet applications, individuals are anxious about the risks presented when engaging in online activities or transactions (Pavlou, 2003; Wu & Wang, 2005). An individual's risk perceptions about technology plays a significant role in their acceptance of that technology (Li, Wang, Wang & Zhou, 2019).

Using a chatbot comes with certain risks. A data privacy risk, for instance, which is introduced when the chatbot interacts with various users, posing the risk that sensitive information may be shared with one user without having obtained consent from the respective user, and using that data as training data (Fraser, 2023).

Once individuals learn that the adoption and use of a certain technology could potentially have negative consequences, they will avoid these consequences by ceasing to use that technology (Chiu et al., 2014). The relationship between PR and BI has historically been validated as negative in prior studies and is therefore hypothesized as such in this study as well (Pavlou, 2003; Wu & Wang, 2005; Li, Wang, Wang & Zhou, 2019). Zhou (2012) also indicated that PT may affect PR.

1.3. Hypothesis 3

H3a: The PR of using chatbots in the South African financial services industry has a direct negative impact on PS.

H3b: The PR of using chatbots in the South African financial services industry has a direct negative impact on PT.

H3c: The UPE of using chatbots in the South African financial services industry negatively mediates the relationship between PR and HPE.

2.3.4 EE

The EE construct defined in UTAUT has a conceptual similarity to the perceived ease of use construct defined by Davis (1989) in TAM. Venkatesh et al. (2003) defined EE as the degree of ease associated with the use of technology. EE has three primary dimensions – perceived ease of use, complexity, and ease of use – which all add up to how easy or complicated it is to use technology (Venkatesh et al., 2003). TAM posits that, the easier technology is to use, the more useful it is perceived to be (Davis, 1989).

Using chatbots reduces the effort that one must endure when interacting with a service provider (Gartner, 2020). Using chatbots allows individuals to circumvent the effort of contacting service providers through call centres or in person. The convenience of chatbots leads individuals to either flock towards them, or to shy away (Lu, Cai & Gursoy, 2019; Monzon, 2021).

Although the UTAUT considers EE to be a significant determinant of BI (Venkatesh et al, 2003; Chao, 2019), Liébana-Cabanillas, Sánchez-Fernández and Muñoz-Leiva (2014) failed to find a significant relationship between EE and BI. However, this study maintained that EE affects the BI to adopt, and as such, the EE construct is hypothesized under the direct and indirect impacts of ATT, SE, and PT in this study.

2.3.5 UPE

The UTAUT presented PE as a core variable to determine BI and it is defined as the degree to which an individual believes that using technology will help them achieve a favourable outcome (Venkatesh et al., 2003). The PE construct in UTAUT is aligned to the perceived usefulness construct of TAM (Venkatesh et al., 2003). Perceived usefulness is defined as the potential individual's subjective belief that using a particular technology would enhance their job performance (Davis, Bagozzi & Warshaw, 1989).

Yang (2010) however split the PE construct into two dimensions, arguing that BI may be driven by task performance (i.e., utilitarian aspects) and entertainment aspects (i.e., hedonic aspects). According to Yang (2010), splitting the PE construct into hedonic and utilitarian dimensions offered better explanatory power as opposed to a single PE construct. UPE is therefore defined as the degree to which an individual believes that using technology will facilitate them in achieving task performance (Venkatesh et al., 2003; Yang, 2010).

Khalilzadeh, Ozturk and Bilgihan (2017) indicated that enhanced task performance leads to increased satisfaction, which in turn, results in finding the task as being entertaining. Thus, implying that UPE might lead to HPE. The rationale for this argument is that individuals who expect an increase in task performance from using technology, also experience more fun while using the technology (Khalilzadeh, Ozturk & Bilgihan, 2017).

According to Alger (2018), most chatbots cannot provide personalised, human-like interactions. The Facebook chatbot, for instance, only has a 30% success rate when responding to requests without the need for human interaction (Alger, 2018). Ling et al. (2021) indicated that the most frequently reported factor influencing the adoption and usage of chatbots is the utilitarian benefits that an individual derives. Using a chatbot assists individuals to access information promptly and address a query (Ling et al., 2021).

When an individual instructs a chatbot to perform a certain task, a vague or deflecting response is not satisfactory (Simonite, 2017) and will therefore result in a lower UPE (Yang, 2010; Zhao & Bacao, 2020). However, when the chatbot successfully facilitates a task outcome, the UPE is high and therefore users are expected to be more inclined to use chatbots (Yang, 2010).

Lu, Cai and Gursoy (2019) found that UPE – the degree to which chatbots are perceived to complete certain tasks more efficiently than humans – positively influences an individual's willingness to use chatbots.

1.1. Hypothesis 4

Considering the above review, the following is hypothesised:

H4: UPE in using chatbots in the South African financial services industry has a direct positive impact on the HPE of chatbots.

2.3.6 PS

PS is defined as the degree to which an individual believes using technology will be secure (Shin, 2009). There is an expectation that PS affects an individual's ATT and BI to use technology (Khalilzadeh, Ozturk & Bilgihan, 2017).

Security-related aspects are important when considering technology, more so when financial elements are involved (Khalilzadeh, Ozturk & Bilgihan, 2017). For chatbots to operate effectively, they must collect and store data. Individuals should feel safe while interacting with a chatbot, especially in industries such as the financial services industry. Alger (2018) indicated that organisations must ensure that adequate security processes are in place to govern where information is stored, who is using it, and what they are allowed to use it for. Businesses should consider security measures such as the encryption of chatbot communication (Alger, 2018).

An individual's ATT towards technology may influence their perception of security related to the technology and their BI (Khalilzadeh, Ozturk & Bilgihan, 2017). Therefore, ATT may affect the BI to adopt the technology. And, according to Khalilzadeh, Ozturk and Bilgihan (2017), individuals generally develop perceptions of security over a period. Individuals gauge the security of technology based on the successes and failures of that technology, as well as public opinion and influences from their social circles (Khalilzadeh, Ozturk & Bilgihan, 2017).

Khalilzadeh, Ozturk and Bilgihan (2017) indicated that security may be viewed as a predecessor of an individual's ATT and BI.

1.2. Hypothesis 5

H5a: ATT towards using chatbots in the South African financial services industry positively mediates the relationship between PS and BI to use chatbots.

H5b: SI of accepting chatbots in the South African financial services industry positively and directly influences PS.

2.3.7 SE

Compeau and Higgins (1995) described SE as the belief that an individual can perform a certain behaviour. Venkatesh (2000) later described it as the degree to which an individual believes that they can perform an action or task using technology.

The perceptions of SE have been found to affect an individual's decisions about which behaviour to carry out (Compeau & Higgins, 1995; Maillet, Mathieu & Sicotte, 2015). Blut, Wang and Schoefer (2016) highlighted that when individuals have experience and compatibility with technology, their knowledge of the technology and confidence in the ability to use the technology becomes a basis for the acceptance and adoption of that technology. An individual with high SE for a certain technology is expected to have higher BI to continue using that technology (Kajol, Singh & Paul, 2022).

The SE construct was removed from UTAUT due to a full mediation effect from the EE construct (Venkatesh et al., 2003). An indirect relationship between SE and EE was however studied by Venkatesh (2000).

1.3. Hypothesis 6

H6: An individual's SE perceptions negatively and directly affect the amount of EE in learning and using chatbots in the South African financial services industry.

2.3.8 PT

There appears to be some confusion about how users understand and perceive the concept of trust concerning technology (Alwabel & Zeng, 2021). However, Wu and Chen (2005) stated that trust in online contexts implies the belief that an organisation will fulfil commitments without taking advantage of the end-user. Similarly, Alwabel and Zeng (2021) defined trust as an individual's belief that technology will perform as expected. Technology service providers must fulfil their promises and not deceive users (Zhou, 2012). This notion therefore implies a possible relationship between PT and performance expectations.

Various prior studies have evaluated the effect of trust on BI and technology adoption. For example, Gefen, Karahanna and Straub (2003) studied the effect of trust in online shopping contexts and indicated that the perception of trust increases as individuals increasingly engage technology.

Studies by Shin (2009) and Pillai, Kim, Haldorai and Kim (2022) found a significant relationship between PT and BI and emphasized the role of security and trust perception on BI. Alwabel and Zeng (2021) outlined a possible relationship between PT and PS by stating that an individual's perceptions of trust in technology is conceptualised in its ability to safeguard sensitive information and the security measures offered by the technology.

1.4. Hypothesis 7

H7a: PS of chatbots in the South African financial services industry positively and directly predicts PT.

H7b: PT in chatbots in the South African financial services industry directly increases the amount of EE tolerance individuals need to continue learning and using chatbots.

H7c: PT in chatbots in the South African financial services industry positively and directly predicts the BI to use chatbots.

H7d: PT for chatbots in the South African financial services industry positively impacts HPE.

H7e: PT for chatbots in the South African financial services industry positively impacts UPE.

2.3.9 SI

The SI construct in technology acceptance models has been researched for several years. Venkatesh et al. (2003) defined it as the degree to which an individual perceives that significant others believe one should use new technology. The SI construct in UTAUT is conceptually and empirically similar to the subjective norm construct in TAM (Venkatesh et al., 2003). Kajol, Singh and Paul (2022) defined SI as the degree to which people base their opinion and use of a technology depending on the opinions of people surrounding them. There are social pressures that individuals might face when performing a certain action (Alwabel & Zeng, 2021).

An important consideration of the SI construct is image - the extent to which using technology is perceived to enhance one's social status (Moore & Benbasat, 1991). Individuals are inclined to use technology that enhances their social status and image (Alwabel & Zeng, 2021). Social norms have been established to influence behavioural technology (Chan, Troshani, Hill & Hoffmann, 2022).

An individual’s social circle may influence one about the entertainment or usefulness of technology. De Luna, Liébana-Cabanillas, Sánchez-Fernández and Muñoz-Leiva (2019) as well as Khalilzadeh, Ozturk and Bilgihan (2017) positioned a possible relationship between SI and HPE and UPE.

Social factors may also be important antecedents to accepting or using novel technologies (Ling et al., 2021). UTAUT posits that SI has a direct positive impact on an individual’s BI to adopt technology (Venkatesh et al., 2003; Khalilzadeh, Ozturk & Bilgihan, 2017).

Ling et al. (2021) indicated that the use of chatbots increases when individuals perceive that their association with chatbots will improve their social status or image.

1.5. Hypothesis 8

In consideration of the above review, the hypotheses about the SI construct are as follows:

H8a: The SI of accepting chatbots in the South African financial services industry positively affects the BI to use chatbots.

H8b: The SI of accepting chatbots in the South African financial services industry directly and positively impacts HPE related to chatbots.

H8c: The SI of accepting chatbots in the South African financial services industry directly and positively impacts UPE related to chatbots.

2.3.10 HPE

UTAUT introduced PE as a variable to determine BI to accept technology (Venkatesh et al., 2003), following which, Yang (2010) made the distinction between HPE and UPE. This distinction was made because UTAUT measures UPE, but neglects to consider hedonic elements (Venkatesh et al., 2003; Yang, 2010). In a later development however, UTAUT2 introduced hedonic motivation as a construct and used enjoyment, entertainment and fun associated with the technology as measurement items of this construct (Venkatesh, Thong & Xu, 2012).

According to Davis, Bagozzi and Warshaw (1992), and Yang (2010), HPE is the degree to which an individual believes that using technology will be fun or pleasurable. HPE has historically been conceptualised as perceived enjoyment (Zhang, Zhu & Liu, 2012) or intrinsic motivation (Davis, Bagozzi & Warshaw, 1992). Zhang, Ziu and Liu (2012) defined HPE as the intrinsic reward derived through the use of technology.

In a study focused on hedonic and utilitarian technologies, van der Heijden (2004) found that enjoyment is more significant for determining an individual's acceptance of hedonic technologies than it is for utilitarian technologies. Yang (2010) argued that compared to other determinants of BI, hedonic motivations and entertainment elements are the most critical drivers of BI. Zhang, Zhu and Liu (2012) also indicated that the greater the entertainment value and fun technology brings to an individual, the greater the BI to accept that technology.

Although UPE and HPE were measured as separate constructs, Khalilzadeh, Ozturk and Bilgihan (2017) contended that there is a possible relationship to explore between the two. Their argument indicated that an enhancement in task performance or task outcomes increases one's satisfaction, which results in the individual viewing the task as enjoyable (Khalilzadeh, Ozturk & Bilgihan, 2017).

This notion introduced a possible relationship to investigate as it implies that UPE might lead to HPE – users who expect increased task fulfilment by technology, also experience more joy from using the technology (Khalilzadeh, Ozturk & Bilgihan, 2017).

The level of fun and enjoyment, represented by the HPE construct is under the direct and indirect impact of several factors including ATT, PT, UPE, PR, and SI.

2.4 BI TO ADOPT TECHNOLOGY

This section is a literature review of BI as a construct related to technology adoption and helps to build a foundation for the hypotheses development to address research objective (ii).

2.4.1 BI

BI is a concept that has been extensively studied in context to predicting future behaviour, especially within the TRA framework introduced by Fishbein and Azjen (1975; 1980).

An individual's intention to use technology is best predicted by behaviour (Shin, 2009). BI is the central dimension of the UTAUT and TAM, and it is defined as a measure of the strength of an individual's intention to act on behaviour (Fishbein and Ajzen, 1974; Venkatesh et al., 2003). It is one of the significant dependent variables (DV) in technology acceptance theories (Muk & Chung, 2014; Mohammadi, 2015).

Warshaw and Davis (1985) defined BI as the degree to which an individual formulates a plan to perform or not perform a certain action in future (Warshaw & Davis, 1985). TAM assumes that individuals who believe technology will be useful to them, are more likely to display positive BI to use that technology (Davis, 1986; Blut, Wang & Schoefer, 2016).

The adoption models underlying the UTAUT all suggest that BI will have a significant positive influence on the use of technology (Venkatesh et al., 2003). However, similar to Khalilzadeh, Ozturk and Bilgihan (2017), this study uses BI as a proxy for the actual use of technology.

The BI construct is under the direct and indirect impact of several factors including PS, FC, ATT, PT, and SI.

2.5 MODERATING EFFECTS OF AGE, GENDER AND PREVIOUS EXPERIENCE AFFECTING THE ADOPTION OF TECHNOLOGY

This section presents the literature review for the moderating variables of age, gender, and previous experience, and assists in the hypotheses development to address research objective (iii).

2.5.1 AGE, GENDER, AND PREVIOUS EXPERIENCE

Demographic factors have generally been found to not be direct determinants of BI (Blut, Wang & Schoefer, 2016). However as posited in UTAUT, these factors are more effective as moderator variables (Venkatesh et al., 2003). A moderating variable affects the relationship between two other variables (Field, 2018).

Moderating variables in the UTAUT are important components (Khalilzadeh, Ozturk & Bilgihan, 2017; Liu & Tao, 2022). The UTAUT has four moderating variables age, gender, experience, and voluntary use (Venkatesh et al., 2003). However, the moderating variables examined for UTAUT in previous studies have found that only age, gender, and experience are the most significant and influential (Im, Hong & Kang, 2011; Baptista and Oliveira, 2015). As such, this study adopts only age, gender, and previous experience as moderating variables.

Older people are more likely to encounter challenges when processing new or complex information, which in turn affects their ability to learn new technologies (Blut, Wang & Schoefer, 2016). Examining the moderating effects of gender offers researchers insights and an improved understanding of how gender influences technology adoption (Leong, Ooi, Chong & Lin, 2013). Venkatesh and Morris (2000) indicated that as experience with technology increases over time, individuals develop a better assessment of the benefits and costs associated with the technology.

Moderating variables, sometimes referred to as control variables, are a third variable that affect the direction or strength of the relationship between an IV and DV (Baron &

Kenny, 1986). According to Baron and Kenny (1986) a moderating variable can be qualitative in nature such as gender and race, or quantitative, such as level of income.

The effect of a moderating variable in statistical terms is that the relationship between the independent variable (IV) and the dependent variable (DV) differs in strength or direction at different values of the moderating variable (Shin, 2009).

1.6. Hypothesis for moderating variables

1.6.1. Hypothesis 9

H9: Gender, age and previous experience moderates the BI relationships in the research model.

2.6 ANALYTICAL FRAMEWORK

The analytical framework section provides an integrated view of the theories that underpinned this research in the theoretical framework sub-section, and the conceptual framework that was applied in this study.

2.6.1 THEORETICAL FRAMEWORK

The theoretical framework section presents the broader theories, TAM and UTAUT, that have guided the research objectives of this study and the hypotheses.

2.6.1.1 TAM

TAM, introduced by Davis (1986) is an adaptation of the Theory of Reasoned Action (TRA) tailored for user acceptance of information systems. The goal of TAM is to provide an explanation of the determinants of acceptance across a broad range of end-user computing technology (Davis, Bagozzi & Warshaw, 1989). TAM posits two constructs – perceived usefulness and perceived ease of use – as being important in determining an individual’s acceptance of technology (Davis, Bagozzi & Warshaw, 1989). Perceived usefulness refers to the degree to which individuals believe that using technology will improve their work performance, and perceived ease of use refers to the degree to which individuals believe that using technology will be free of effort (Li, Wang, Wang & Zhou, 2019).

TAM further postulates that ATT towards using technology directly determines BI to use technology, which in turn, determines actual use of technology (Davis, Bagozzi & Warshaw, 1989).

TAM is the most extensively used and acknowledged framework in technology adoption research (Kajol, Singh & Paul, 2022). According to Li, Wang, Wang and Zhou (2019) this is because TAM is simple, highly efficient and has a high predictive ability. TAM has been successfully applied in studies that investigate an individual’s BI to adopt new technology (Lai & Li, 2005; Yi, Jackson, Park & Probst, 2006; Saade & Bahli, 2005; Shin, 2009; Liébana-Cabanillas, Sánchez-Fernández & Muñoz-Leiva, 2014; Muk & Chung, 2014; Mohammadi, 2015; Blut, Wang & Schoefer, 2016; Li, Wang, Wang & Zhou, 2019). According to a review conducted and synthesized by Ling et al. (2021) most studies investigating the acceptance and use of technology are dominated by references to TAM and its subsequent modifications.

In several studies, the application of TAM has been extended by incorporating additional constructs or theories. Wu and Wang (2005) extended TAM by integrating the Innovation Diffusion Theory (IDT), PR, and cost to determine an individual’s acceptance of mobile commerce. Saadé and Bahli (2005) extended TAM by including cognitive absorption to investigate the adoption and acceptance of online learning systems. Fang, Chan, Brzezinski and Xu (2005) used task type in mobile commerce as a moderating variable in the application of TAM. Liébana-Cabanillas, Sánchez-Fernández and Muñoz-Leiva (2014) extended TAM by incorporating the variables of trust and risk.

In another study, Blut, Wang and Schoefer (2016) presented a meta-analysis of the factors that determine individual acceptance of self-service technologies by integrating TAM with the IDT and UTAUT and using cultural dimensions as moderating factors in the study. And more recently, Li et al. (2019) studied the acceptance of mobile payments by adding PR to TAM.

2.6.1.2 UTAUT

The UTAUT model is an important concept in the field of technology acceptance because it integrated eight major theories and was tested on a large data set (Venkatesh et al., 2003).

The UTAUT created a strong base for acceptance studies since it was introduced (Baptista & Oliveira, 2015). It consists of four core variables – PE, EE, SI, and FC – which directly determine BI and technology usage, as well as four moderating variables – age, gender, experience, and voluntariness of use (Venkatesh et al., 2003). UTAUT has two more constructs compared to TAM – FC, which are environmental factors that make a certain task easier, and SI, which is the degree to which an individual perceives that important others believe that they must adopt technology (Venkatesh et al., 2003; Im, Hong & Kang, 2011).

UTAUT has been vastly applied to technology acceptance studies, and the model has been validated by numerous recent studies (for example, Zhou, Lu & Wang, 2010; Im, Hong & Kang, 2011; Baptista & Oliveira, 2015; Jung, Kwon & Kim, 2020).

It is noteworthy to mention that Venkatesh, Thong, and Xu (2012) later proposed UTAUT2, an extension of the UTAUT, which incorporated three new constructs – hedonic motivation, price value, and habit, and is more tailored to consumer-use contexts. UTAUT2 is however out of scope for this research.

2.6.1.3 OTHER RELATED THEORETICAL FRAMEWORKS

Understanding technology adoption and acceptance is a research area that has been studied for years and has yielded numerous models with different sets of acceptance determinants (Moore & Benbasat; 1991; Venkatesh, Morris, Davis & Davis, 2003).

Although this study is grounded on the constructs of UTAUT and TAM, other related frameworks are worth mentioning.

The Innovation Diffusion Theory (IDT) was introduced by Moore and Benbasat (1991) and holds that an individual's decision to adopt technology is driven by five major characteristics – relative advantage, complexity, observability, compatibility and trialability.

The Theory of Reasoned Action (TRA) introduced by Fishbein and Azjen (1975) was drawn from social psychology, and it is another instrumental technology adoption model. TRA is grounded on the links between the beliefs, attitudes, norms, intentions, and behaviours of individuals (Baptista & Oliveira, 2015). According to the TRA, an individual's behaviour is determined by their BI to perform a task or action, which in turn is determined by their ATT and their subjective norms towards the behaviour (Fishbein & Azjen, 1975).

The Theory of Planned Behaviour (TPB) is an extension of TRA, and unlike TRA, TPB considered that individuals do not always have control over their behaviours (Azjen, 1991; Baptista & Oliveira, 2015). TPB extended TRA by adding perceived behavioural control as a determinant – the perceived ease or difficulty of performing the behaviour. TPB discusses that technology adoption is preceded by BI which in turn is determined by the individual's ATT, their beliefs about the extent to which they can control a particular behaviour, and other external factors (Azjen, 1991).

The Model of Personal Computer Utilisation (MPCU) developed by Thompson, Higgins and Howell (1991) offered a competing perspective to the TRA and TPB. MPCU was used to predict computer utilisation in an organisational context and found that social norms, the complexity of using computers, fit between the job and computer capabilities, and long-term consequences strongly influence computer utilisation (Thompson, Higgins & Howell, 1991).

The Motivational Model (MM) was derived from general motivational theory typically applied in psychology, and expanded on by Davis, Bagozzi and Warshaw (1992). The MM sought to determine whether individuals use computers in the workplace because they are useful, or because they are enjoyable to use. This body of work highlighted two core constructs - extrinsic motivation, which reflects the usefulness of the technology, and intrinsic motivation, which reflects the enjoyment of using the technology – as factors that determine BI to use computers in the workplace (Davis, Bagozzi & Warshaw, 1992).

Compeau and Higgins (1995) extended Albert Bandura's (1986) body of work on Social Cognitive Theory (SCT) and examined the relationship between SE and an individual's use of computers. SE was found to be a significant determinant of the actual use of computers (Compeau & Higgins, 1995). And the last related theoretical framework to mention is a combination of TAM and TPB (C-TAM-TPB) wherein Taylor and Todd (1995) sought to compare which model, between TAM and TPB, best explains the usage of technology.

2.6.2 CONCEPTUAL FRAMEWORK

Following from the literature reviewed and discussed above, this study adopted the conceptual framework by Khalilzadeh, Ozturk and Bilgihan (2017) and illustrated in Figure 2. A conceptual framework represents an interrelated set of variables and depicts the hypotheses that illustrate the relationship between the variables that stem from the theoretical framework (Creswell & Creswell, 2018).

The conceptual framework in this research is a combination of the constructs of UTAUT, and the SE and ATT constructs from TAM, as well as security-related constructs – PR, PS, and PT. The constructs of the framework are moderated by age, gender, and previous experience, and this conceptual framework uses BI as a proxy for user behaviour (Khalilzadeh, Ozturk & Bilgihan, 2017).

The paths and relationships in this conceptual framework are complicated because one variable can affect another variable but are moderated or mediated by another variable. Some relationships are however straightforward wherein one variable affects another variable directly. Therefore, only direct relationships are depicted in the below conceptual framework, and a + or – is in parenthesis to indicate a hypothesised positive or negative relationship, respectively. The unlabelled paths in the diagram have either a moderating variable, or a mediating variable and were therefore challenging to diagrammatically depict.

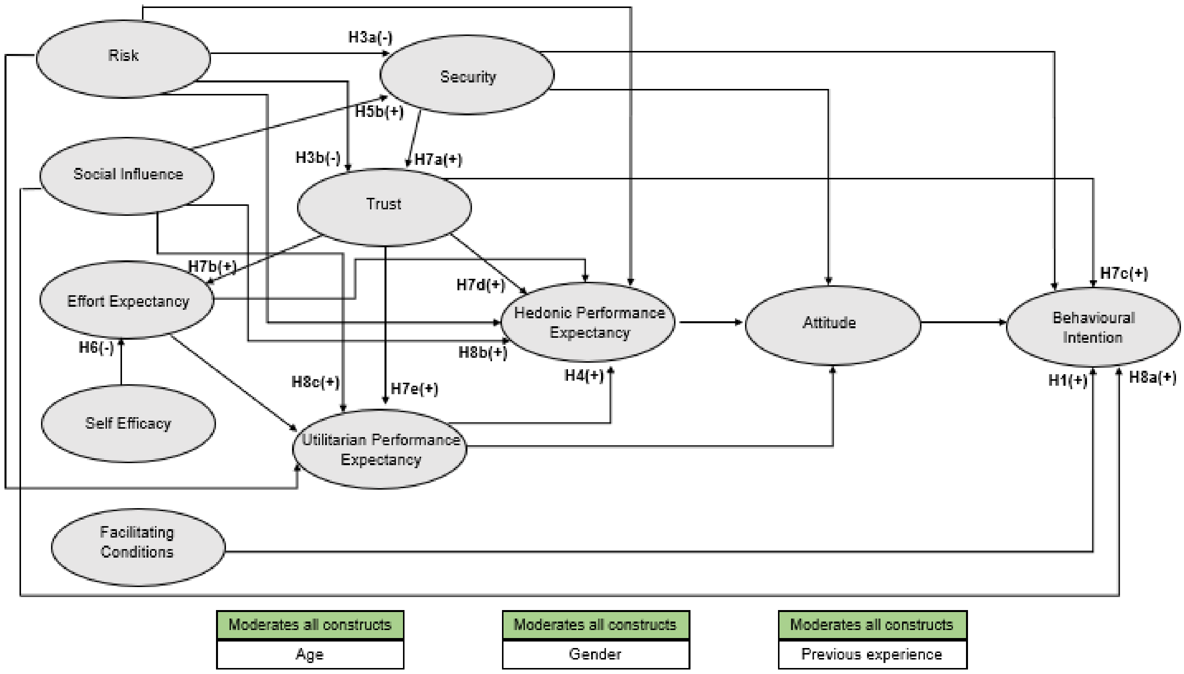


Figure 2: Conceptual framework for this study with hypotheses (Khalilzadeh, Ozturk and Bilgihan, 2017)

2.7 CONCEPTUAL FRAMEWORK SYNTHESIS FOR THE CURRENT STUDY

Several studies have validated the constructs of TAM and UTAUT theoretical frameworks, and since inception, TAM and UTAUT have been extensively applied in explaining the adoption of technologies by individuals. In fact, according to a literature review conducted by Teng and Khong (2021), the most used research models are indeed TAM and UTAUT. In addition to the factors in these two models, PR and trust are constructs that are often used to supplement the existing constructs of TAM and UTAUT (Liébana-Cabanillas, Sánchez-Fernández & Muñoz-Leiva, 2014; Teng & Khong, 2021).

Some researchers have, however, rejected the relationships and theories of TAM and UTAUT. For instance, Dwivedi et al. (2019) argued that the moderating variables in UTAUT may not be applicable in all contexts. This stance was developed by Venkatesh, Thong and Xu (2012) who stated that most studies that applied the UTAUT had dropped the moderating variables.

Another criticism of the UTAUT is the relationship between FC and BI. In the UTAUT, Venkatesh et al. (2003) disregarded the direct relationship between FC and BI, stating that EE has a more significant direct relationship to BI, and that FC would have an impact on BI only in the absence of EE. In contrast to this view, Dwivedi et al. (2019) disagreed, ad proposed that the relationship between FC and BI should be explored, even in the presence of EE.

One more criticism of applying the UTAUT alone is that although all the four core constructs – PE, EE, SI, and FC – significantly explain the adoption and BI to use technology, the model is missing a key element as it neglects the characteristics of the individual engaging the technology (Dwivedi et al., 2019). The characteristics of the individual using the technology may also offer explanations about the BI. Khalilzadeh, Ozturk and Biligihan (2017) integrated the constructs of ATT and SE to fill this gap. The inclusion of ATT as a construct is also consistent with the TRA and TPB frameworks and helped to improve the accuracy of the UTAUT (Fishbein & Azjen, 1975; Azjen, 1991; Venkatesh et al., 2003; Khalilzadeh, Ozturk & Biligihan, 2017).

And on the other hand, some researchers have found it more valuable to combine constructs from different frameworks in their studies. Zhou, Lu and Wang (2010) indicated that integrating frameworks and theories have the potential to provide richer insights. Baptista and Oliveira (2015) combined the UTAUT with cultural dimensions to study the acceptance of mobile banking in Mozambique. Khalilzadeh, Ozturk and Bilgihan (2017) combined constructs from UTAUT, SE, and the ATT construct of TAM, as well as security-related constructs to explain the acceptance of near-field communication technology and found this to have been a valuable conceptual framework as it explained 87% of near-field communication acceptance.

Although often described as simple, TAM has high predictive power when it comes to the acceptance of novel technologies (Liang, Eccarius & Lu, 2019). Previous literature has demonstrated the suitability of TAM in studying technology acceptance across a variety of technologies. Shin (2009), Mohammadi (2015), Blut, Wang and Schoefer (2016) are some of the few researchers who have validated the constructs of TAM.

There is, however, an observed trend for researchers to extend TAM with other constructs from the UTAUT (Shin, 2009). Leong, Ooi, Chong and Lin (2013) assert that TAM has generally been applied as a foundational framework in technology adoption studies, and researchers expand it by incorporating additional variables. Extending TAM with constructs from UTAUT is often justified as the model neglects the social contexts in which technology is accepted and used – a gap that integrating UTAUT fills as it considers the effect of SI as a determinant of technology adoption (Shin, 2009).

Comparable to Khalilzadeh, Ozturk and Bilgihan's (2017) study, this research was grounded on the UTAUT and the SE and ATT constructs of TAM, as well as security-related constructs, to investigate the factors that affect the adoption of chatbots in the South African financial industry.

This conceptual framework was expected to produce rich research insights and address the shortcomings of applying the two models separately. Khalilzadeh, Ozturk and Bilgihan's (2017) study validated that adding SE, ATT, and security-related constructs to the conceptual framework improved the explanatory power and accuracy of the UTAUT model. Their research provided better explanatory power and predictive accuracy than the UTAUT model alone (Khalilzadeh, Ozturk & Bilgihan, 2017). It is therefore the intent of this research to determine if the same conceptual framework can be validated in the context of the South African financial services industry for the adoption and acceptance of chatbots.

2.8 CONCLUSION

The above literature review provides a strong indication that FC, ATT, PR, EE, UPE, PS, SE, PT, SI, and HPE are factors that could affect the BI to adopt chatbots. The literature review also indicates that there may be differences in the relationship between these factors based on the age, gender, and previous experience of the individual.

Proceeding from the above literature review, the hypotheses for this study are as follows:

HYPOTHESIS 1: The FC for using chatbots in the South African financial services industry positively affect BI to use chatbots.

HYPOTHESIS 2a: HPE from using chatbots in the South African financial services industry positively mediates the effect of EE on ATT towards using chatbots.

HYPOTHESIS 2b: UPE from using chatbots in the South African financial services industry positively mediates the effect of EE on ATT towards using chatbots.

HYPOTHESIS 2c: ATT towards using chatbots in the South African financial services industry positively mediates the relationship between HPE and BI to use chatbots.

HYPOTHESIS 2d: ATT towards using chatbots in the South African financial services industry positively mediates the relationship between UPE and BI to use chatbots.

HYPOTHESIS 3a: The PR of using chatbots in the South African financial services industry has a direct negative impact on PS.

HYPOTHESIS 3b: The PR of using chatbots in the South African financial services industry has a direct negative impact on PT.

HYPOTHESIS 3c: The UPE of using chatbots in the South African financial services industry negatively mediates the relationship between PR and HPE.

HYPOTHESIS 4: UPE in using chatbots in the South African financial services industry has a direct positive impact on the HPE of chatbots.

HYPOTHESIS 5a: ATT towards using chatbots in the South African financial services industry positively mediates the relationship between PS and BI to use chatbots.

HYPOTHESIS 5b: SI of accepting chatbots in the South African financial services industry positively and directly influences PS.

HYPOTHESIS 6: An individual's SE perceptions negatively and directly affect the amount of EE in learning and using chatbots in the South African financial services industry.

HYPOTHESIS 7a: PS of chatbots in the South African financial services industry positively and directly predicts PT.

HYPOTHESIS 7b: PT in chatbots in the South African financial services industry directly increases the amount of EE tolerance individuals need to continue learning and using chatbots.

HYPOTHESIS 7c: PT in chatbots in the South African financial services industry positively and directly predicts the BI to use chatbots.

HYPOTHESIS 7d: PT for chatbots in the South African financial services industry positively impacts HPE.

HYPOTHESIS 7e: PT for chatbots in the South African financial services industry positively impacts UPE.

HYPOTHESIS 8a: The SI of accepting chatbots in the South African financial services industry positively affects the BI to use chatbots.

HYPOTHESIS 8b: The SI of accepting chatbots in the South African financial services industry directly and positively impacts HPE related to chatbots.

HYPOTHESIS 8c: The SI of accepting chatbots in the South African financial services industry directly and positively impacts UPE related to chatbots.

HYPOTHESIS 9: Gender, age, and previous chatbot experience moderates the BI relationships in the research model.

3 CHAPTER 3. RESEARCH METHODOLOGY

This chapter describes the methodology and approach that was followed to address the hypotheses that ensued from the literature reviewed in Chapter 2 and to achieve the research objectives outlined in Chapter 1. The research approach, research design, data collection methods, data interpretation strategies, and population sampling aspects are discussed herein. This chapter concludes by detailing the quality assurance characteristics of this research, and ethical considerations about this study.

3.1 RESEARCH APPROACH

To achieve the research objectives of this study, a quantitative research approach was adopted. According to Creswell and Creswell (2018), quantitative research is suitable in instances where the research must identify factors that influence an outcome, and where the research aims to gain an understanding of the best predictors of an outcome.

A quantitative research approach was best applicable for this study as it allowed for the identification of factors that affect the adoption of chatbots in the South African financial services industry, based on the UTAUT constructs, ATT from TAM, SE and security-related constructs, and offered an understanding of the predictors of an individual's BI to use chatbots (Creswell & Creswell, 2018).

A quantitative research approach is most appropriate for determining the factors that influence a certain behaviour because it allows the relationship between variables to be examined (Creswell & Creswell, 2018). Most of the literature review on technology adoption also employed a quantitative research approach (for example, Muk & Chung, 2014; Blut, Wang & Schoefer, 2016; Khalilzadeh, Ozturk & Bilgihan, 2017; De Luna et al., 2019; Talukder, Sorwar, Bao, Ahmed & Palash, 2020; Zhao & Bacao, 2020).

3.1.1 ASSUMPTIONS OF THE RESEARCH APPROACH

i. A quantitative research approach assumes that there is a logical cause-and-effect relationship between the variables in the conceptual framework (Balnaves & Caputi, 2001; Creswell & Creswell, 2018).
ii. A quantitative research approach assumes that there is evidence that can be observed and statistically tested (Balnaves & Caputi, 2001). This assumption is appropriate for this study because evidence related to the factors that affect chatbot adoption will ensure that the research objectives are achieved.

3.2 RESEARCH DESIGN

An online questionnaire was best suited to achieve the research objectives outlined in Chapter 1. The online, self-administered questionnaire was designed using Qualtrics. A questionnaire is the best-suited research design because it allowed for this study to test for relationships among the variables of the conceptual framework within the South African financial services industry regarding the adoption of chatbots (Creswell & Creswell, 2018).

Venkatesh et al. (2003) state that technology acceptance studies have historically been conducted using survey, or questionnaire research designs. For example, recent technology acceptance studies conducted by Khalilzadeh, Ozturk and Bilgihan (2017), Liang, Eccarius and Lu (2019), as well as Talukder, Sorwar, Bao, Ahmed and Palash (2020) have also employed a questionnaire research design.

A questionnaire allowed for a description of trends, ATTs, and opinions of the population in this study (Creswell & Creswell, 2018). In addition, a questionnaire research design allowed for the analysis of descriptive characteristics of the population and predictive relationships between the variables of the conceptual framework, and the population (Creswell & Creswell, 2018).

3.2.1 ADVANTAGES OF THE RESEARCH DESIGN

i. An online questionnaire made it possible to reach numerous potential participants.
ii. An online questionnaire allowed for rapid turnaround in data collection (Creswell & Creswell, 2018). The target responses were achieved within 8 weeks, by of March 2023.
iii. An online questionnaire come with a relatively low cost of administration (Couper, 2000).
iv. A questionnaire research design allowed for predictive relationships to be analysed between the variables of the conceptual framework, and the population.
v. A survey research design produced seminal research results in numerous technology adoption studies, and it is commonly used in technology adoption studies (Venkatesh et al., 2003; Wu & Wang, 2005; Im, Hong & Kang, 2011; Khalilzadeh, Ozturk and Bilgihan, 2017).

3.2.2 DISADVANTAGES OF THE RESEARCH DESIGN

i. Survey research designs are generally subject to bias and error (Balnaves & Caputi, 2001).
ii. An online survey generally has little control over multiple completions (Couper, 2000). Multiple responses to the questionnaire could potentially affect the integrity of the research. However, multiple responses from a user were disabled in the Qualtrics platform prior to distributing the questionnaire.

3.3 DATA COLLECTION METHODS

The data collection method employed for this research was by means of a cross-sectional online questionnaire as data was collected at one point in time; during the first quarter of 2023 (Creswell & Creswell, 2018).

An online platform was selected for this study since users of digital technologies, and chatbots, are frequent users of online resources. The target sample size for this research was 300, and a questionnaire made it possible to reach numerous potential respondents, and to be able to address the research objectives of this study. A questionnaire design also allowed for standardisation of measurement items adapted from previous literature.

The questionnaire was designed using Qualtrics. Qualtrics was selected for this study because it is a commonly used questionnaire online platform and the University of Witwatersrand provided user licences for the platform. The questionnaire was distributed across social media platforms, instant messaging platforms and emails.

3.4 POPULATION AND SAMPLE

3.4.1 POPULATION

The research population consisted of individuals in South Africa who have resources to complete an online questionnaire, for example, smartphones, laptops, and internet connectivity, irrespective of age, gender, race, or any demographic characteristics.

3.4.2 SAMPLE

It is often impractical to collect data from the whole population, and in South Africa this would be approximately 60 million people (Stats SA, 2022). Therefore, identifying a sample for this study was necessary. Sampling is a technique in research that allows one to select a subset of units of analysis from a population and enables representativeness of that population (Balnaves & Caputi, 2001).

Scholars have provided an array of sample size guidelines, but among the most popular recommendations for minimum sample size is 200 to 500 (Comrey & Lee, 1992). In total, 705 questionnaires were received and after cleaning the data, 265 were discarded as they had missing values. The final sample size achieved in this research was therefore 440 responses.

3.4.3 SAMPLING METHOD

The sampling method used in this research was convenience sampling because respondents were asked to complete the questionnaire based on their availability and accessibility (Creswell & Creswell, 2018). Convenience sampling was executed by sharing the questionnaire link on online platforms such as Linked In, and instant messaging platforms such as What's App and iMessage, as well as through e-mails to allow respondents to complete the questionnaire at a convenient time. The questionnaire link was also distributed to registered students at the University of Witwatersrand, Johannesburg on 1 March 2023 as can be seen by the research permission letter in Appendix D.

Stratification was not necessary for this research as there were no specific respondent characteristics that needed to be represented in the data set (Creswell & Creswell, 2018).

3.5 THE RESEARCH INSTRUMENT

Previous studies were reviewed to ensure that a comprehensive list of research measurement items were included. The items for measuring the research objectives and hypotheses of this study were adapted from Venkatesh et al. (2003) and Khalilzadeh, Ozturk and Bilgihan (2017), to fit the context of chatbot usage in the South African financial services industry. The method to adapt the measurement items was modification of wording to make it relevant to chatbots, and the South African financial services context.

Initially, a pilot questionnaire was designed and distributed to 40 participants. According to Creswell and Creswell (2018) piloting a research instrument is important as it helps to establish the content validity of the scores in the questionnaire, it also provides an evaluation of the internal consistency of the measurement items and helps to improve the format of the final questionnaire to be distributed. Distributing a pilot questionnaire for this research assisted to judge the suitability of the questionnaire and to solicit feedback from participants regarding the questions, format, and instructions in the questionnaire (Creswell & Creswell, 2018).

Based on the feedback received from the pilot testers, some questions in the research instrument were found to be redundant, and some questions were found to be too long. In response, those questions were modified and shortened where needed to ensure clear and concise questions were asked in the final questionnaire. All enhancements to the questionnaire were made bearing in mind that the content validity and internal consistency of the research instrument were not affected.

The final questionnaire that was distributed for this research was in English and it contained three sections. The first section was a brief description of chatbots and the financial services industry. The second section collected general information and demographic characteristics of respondents. The data collected in this section of the questionnaire allowed the analysis of respondent profiles, classification, and other relevant variables which aided in addressing research objective iii and iv.

The third section contained 46 measurement items which assessed the variables of the conceptual framework in the context of chatbot adoption in the South African financial services industry. The measurement items were adapted from Khalilzadeh, Ozturk and Bilgihan (2017), and were used as indicators of variables including FC, ATT, PR, EE, UPE, PS, SE, PT, SI, HPE and BI.

The data collected in the third section of the questionnaire is the core of this research and therefore addressed research objective i and ii. Appendix E shows the measurement items for this study and the supporting literature for each construct.

Each item in the third section of the questionnaire was measured with a 4-point Likert scale being strongly disagree (1), disagree (2), agree (3), and strongly agree (4), and did not include a neutral option. These 4 options are standard categories that are versatile for several response dimensions and commonly used in questionnaires, and therefore placed minimal cognitive burden on the respondents when completing the questionnaire (Schaeffer & Dykema, 2020). The absence of a neutral or central category has been tested by Wang and Krosnick (2019), who indicated that omitting a neutral point does not necessarily help to improve the quality of the data collected or analysed.

The absence of a neutral option in the questionnaire also encouraged respondents to apply cognitive effort when answering the items in the questionnaire and ensured that respondents thought about the merit of the questions before moving on to the next question (Krosnick, 1991; Wang & Krosnick, 2019).

3.6 PROCEDURE FOR DATA COLLECTION

This study was a cross-sectional study and primary data was collected. An online questionnaire platform, Qualtrics, was used to design and distribute the questionnaire. The questionnaire was distributed through Linked In, instant messaging platforms such as What's App and iMessage, as well as via e-mails. Data was collected from the University of Witwatersrand, Johannesburg students as well. The data was collected during February and March 2023.

3.7 DATA ANALYSIS STRATEGIES

Data was collected using Qualtrics and then exported IBM Statistical Package for Social Sciences (SPSS) was for data analysis.

Firstly, the data was screened for missing or incomplete responses. The incomplete or missing responses were discarded which left 440 valid responses for analysis. This number exceeded the sample target for this research and thus it was acceptable.

The data was then assessed for internal validity using exploratory factor analysis (EFA) and discarding unacceptable measurement items. EFA was selected as it reduced the data set collected to a manageable size, while also retaining as much of the original data collected as possible (Field, 2018). Additionally, EFA deemed a good approach to understanding the data collected. The internal consistency of the data was then assessed, per factor. An assessment of the factor matrix was performed using principal axis factoring on SPSS. Principal axis factoring was selected because it caters for related factors. After that, the factors that met the criterion were retained. The retained factors were accepted, and composite scores were created. The composite score function in SPSS allows factors to be combined, and therefore converting into variables or constructs, both terms are acceptable.

The constructs were then assessed for assumptions. In so doing, descriptive statistics were extracted to assess the mean, mode, standard deviation, median and range statistics of the variables. The data was then checked for outliers to ensure that there were no anomalies that drastically stood out.

And finally, to address the research objectives of this study, the variables were used to test the hypotheses developed in Chapter 2.

3.8 DATA INTERPRETATION STRATEGIES

The data analysis and interpretation strategies varied slightly depending on the type of hypothesis. For direct or indirect effect hypothesis, and the moderation hypothesis, a linear regression was performed as well as an analysis of variance (ANOVA). This produced the Pearson correlations, the descriptive statistics, the coefficient effects, and the p-values, and thereby enabling an informed testing of the hypotheses.

The value of the correlation coefficient must lie between -1 and +1, and the interpretation of this value indicates the strength of correlation between the variables (Balnaves & Caputi, 2001; Field, 2018). A value of -1 indicated a perfectly negative correlation, a value of +1 indicated a perfectly positive relationship and a value of 0 indicated no relationship between the variables (Balnaves & Caputi, 2001; Field, 2018). Values of ±0.1 indicate a weak correlation, values of ±0.3 indicate a moderate correlation and values of ±0.7 indicate a strong correlation (Field, 2018).

In some cases, examining the effects of moderating or mediating variables on the dependent or IVs was necessary. A moderating variable is one that affects the relationship between two others (Field, 2018). On the other hand, a mediating variable explains the relationship between an IV and a DV (Field, 2018).

For mediating hypothesis, the PROCESS macro by Andrew Hayes was used on SPSS. A mediation analysis is carried out in instances where the IV affects the DV through an intermediate variable, also referred to as a mediating variable (Msimango-Galawe, 2017). The data interpretation strategy used for the hypotheses with a mediating variable was by using the PROCESS macro by Andrew Hayes in SPSS.

To test the hypotheses in this research, appropriate statistical tests were determined and performed to analyse the data. The research model composed of eleven constructs including SI, PR, UPE, HPE, PT, EE, PS, FC, BI, SE and ATT. Each construct was measured by several items in the questionnaire, and these measurement items were adapted from previous literature (Khalilzadeh, Ozturk & Bilgihan, 2017).

For each construct, the mean and standard deviations were determined. The mean is a measure of central tendency, and it is the average score provided by respondents per construct (Field, 2018). The standard deviation is the square root of the variance, wherein the variance is defined as the average distance of the score from the mean (Field, 2018).

3.9 LIMITATIONS AND CHALLENGES OF THE STUDY

The possible limitations and challenges of this study are listed in this section:

3.9.1 RESEARCH METHODOLOGY LIMITATIONS AND CHALLENGES

a. An individual’s behaviour is dynamic and constantly changing (Zhou, Lu & Wang, 2010). Due to the nature of a cross-sectional study focussing on data collection only at one point in time, this research will not reflect individuals’ perceptions and preferences about chatbots over a long period of time. An individual’s perceptions and preferences are more likely to change as they acquire more experience with technology over time (Mohammadi, 2015).

b. Therefore, this study will unfortunately not provide a long-term view of the determinants of adoption of chatbots, and the view provided in this research did not provide historical or future trends in relation to the adoption of chatbot technology.

c. Some respondents might find a Likert Scale design to be limiting in their response as the survey will not have free-typing fields.

3.9.2 SAMPLE AND SAMPLING METHOD LIMITATIONS AND CHALLENGES

a. This study focused on a sample of individuals in South Africa and was only in relation to chatbots in the financial services industry. This therefore limits the generalisation of the results of this study applied in other countries, industries, and technologies (Creswell & Creswell, 2018; Liébana-Cabanillas, Molinillo & Ruiz-Montañez, 2019).

b. Respondents will be reached via instant messaging platforms and email, that inherently excludes people who have no access to these communication means. As a result, the challenge of this study is that it might not adequately represent the whole South African population.

3.10 QUALITY ASSURANCE

3.10.1 EXTERNAL VALIDITY

External validity, sometimes referred to as generalisation or generalisability, seeks to ascertain whether the study can be generalised and applied to other contexts in addition to the contexts of this research (Creswell, 2014). According to Creswell and Creswell (2018), threats to external validity may arise when the research draws incorrect inferences from the sample data to other settings, other people, and to past or future situations.

To avoid threatening the external validity of this research, generalisation will only be extended to groups with similar characteristics as that of the survey respondents. This approach is suggested by Creswell and Creswell (2018) to restrict claims about population groups to which the research results cannot be generalised.

3.10.2 INTERNAL VALIDITY

Internal validity is concerned with the accuracy of the research instrument itself and it demonstrates the ability of the research instrument to measure its intended purposes if it were repeatedly applied (Creswell, 2014). In a model containing multi-item constructs as it was the case in this study, it is imperative to test the reliability of the constructs (Im, Hong & Kang, 2011; Creswell & Creswell, 2018). Cronbach's α is generally used to verify the internal validity of the construct. Cronbach's α ranges between 0 and 1, with optimal values between 0.7 and 0.9 (Creswell & Creswell, 2018).

In addition to determining Cronbach's α, Exploratory Factor Analysis (EFA) was conducted to test the internal validity of the constructs.

3.10.3 CONSTRUCT VALIDITY

The construct validity provides an indication of whether meaningful and useful inferences can be drawn from the scores in the research model (Creswell & Creswell, 2018). The research model used in this study was adapted from previous studies that tested the validity of the measurement items in this research model (Khalilzadeh, Ozturk & Bilgihan, 2017). Adapting the measurement items from previous items ensured that the construct validity of this research model was preserved (Khalilzadeh, Ozturk & Bilgihan, 2017).

3.10.4 CONSTRUCT RELIABILITY AND CONSISTENCY

The construct reliability and consistency are deemed as one of the most important indications of the reliability of the research model (Creswell & Creswell, 2018). Construct reliability is a measure of the internal consistency of the research instrument measurement items (Zhao & Bacao, 2020), and construct consistency is the degree to which sets of measurement items in a research instrument behave in the same way (Creswell & Creswell, 2018).

To ensure and evaluate the reliability and consistency of the constructs in the research instrument, Cronbach's α was used as an indicator. Cronbach's α provided an estimate for the construct reliability and consistency based on the intercorrelations of the variables in the conceptual framework (Sijtsma, 2009). Ideally, the Cronbach's alpha for each construct being tested should be above 0.7 (Creswell & Creswell, 2018).

3.10.5 RELIABILITY

The reliability of a study ensures that when the same research instrument is applied to a different study, the results will be consistent (Creswell, 2014). It is an assessment of the degree of consistency between multiple measurements of a certain variable (Hair, Black, Babin, Anderson & Tatham, 2006). The objective of reliability is to ensure that responses are not too different across time periods so that measurement items applied at any point in time are reliable (Hair et al., 2006).

The reliability of the research instrument was assessed by determining the Cronbach's α and assessing the correlations between the measurement items in each construct. If the correlation was calculated as 0.3 or below, the measurement item was dropped (Field, 2018).

3.10.6 BIAS

Research instrument bias was carefully observed. The questionnaire was carefully screened against using words or language that may be biased against people because of gender, age, ethnic or racial groups. Additionally, the questionnaire was anonymous, thus allowing participants to be honest in their responses and without hesitation of having their identity revealed.

3.11 ETHICAL CONSIDERATIONS

To guard against any unethical research practices, the purpose of the study was explained to the respondents before they started completing the online questionnaire. Respondents also had to consent to the survey prior to starting it. Additionally, the anonymity of all respondents was made clear in the beginning of the questionnaire survey. And lastly, ethical clearance from the Wits University Ethics Committee was obtained in January 2023 prior to administering the questionnaire. The ethics approval is attached in Appendix C.

3.12 SCHEDULE AND TIMELINES

The research proposal for this study was approved in September 2022, and ethical clearance from the Wits University Ethics Committee was obtained in January 2023. A pilot questionnaire was distributed to a few respondents after the ethics clearance was obtained.

Feedback from the pilot questionnaire was then incorporated into the final questionnaire which was distributed during February and March 2023. The data analysis commenced in April 2023 and the research report was finalised and submitted to the University of Witwatersrand by the end of June 2023.

4 CHAPTER 4. PRESENTATION OF RESULTS

4.1 INTRODUCTION

This chapter presents the results of this research. The results will be presented per hypothesis outlined in chapter 2. Firstly, assumptions are checked for the data collected, and testing of the measurement model is presented prior to providing the results per hypothesis. A summary of findings will be provided at the end of the chapter. SPSS version 28 was used to analyse and present the data from the online questionnaire. The tables and graphs in this chapter were created using SPSS version 28 and Microsoft Office applications.

4.2 DATA QUALITY ASSESSMENTS

The survey results were imported from Qualtrics into SPSS to commence the data analysis process. Before the data analysis was performed however, the data was screened for incomplete questionnaire submissions. A total of 705 questionnaires were received altogether, however 265 submissions had missing data entries and were therefore deleted from the SPSS file prior to analysing the data. The final data set therefore consisted of 440 complete questionnaires and met the target sample size for this research.

The data was checked to ensure that the coding of the options in the questionnaire such as Likert scale values, gender selection and race selection was logical and assigned the correct code to represent the data. The next step was to name the variables in SPSS, specify the data type of the variable, and to label the variables.

4.3 RESPONSE RATE

Table 4-01 shows that a total of 705 online questionnaires were distributed and 440 useful samples were obtained after excluding incomplete surveys, therefore yielding an effective response rate of 62.4%.

Table 4-01: Survey completion statistics

		Number of responses	**Percent complete**
Valid	Complete	440	62.4
	Incomplete	265	37.6
	Total	705	100.0

Source: Author's calculations

4.4 SAMPLE CHARACTERISTICS

This section presents the gender, race, age, education levels, and chatbot usage frequency of the sample of this research.

4.4.1 GENDER

The sample characteristics revealed that 55.5% of the respondents were female, 41.8% were male, 2.5% preferred not to specify their gender, and 0.2% were non-binary, as shown in Table 4-02.

Table 4-02: Gender of the respondents

		Count	Percent
Valid	Female	244	55.5
	Male	184	41.8
	Prefer not to say	11	2.5
	Non-binary / third gender	1	0.2
	Total	440	100.0

Source: Author's calculations

4.4.2 RACE

Table 4-03 shows that most of the respondents were Black, with 342 of the respondents representing 77.7% in the overall sample. This was followed by 32 Whites (7.3%) and 28 Indians (6.4%). 5.9% of the respondents preferred not to indicate their race, and the remaining 2.5% were Mixed Race.

Table 4-03: Race of respondents

		Count	Percent
Valid	Black	342	77.7
	White	32	7.3
	Indian	28	6.4
	Prefer not to say	26	5.9
	Mixed race	12	2.5
	Total	440	100.0

Source: Author's calculations

4.4.3 AGE

Table 4-04 demonstrates that 43.9% of the respondents were in the 26-35 age group and 23% in the 18-25 age group. These two age groups combined made up 66.9% of the sample and therefore indicating that most of the survey respondents were youth. 23.6% were in the 36-45 age group, 5% in the 46-55 age group, 2.3% were under 18, 1.4% were in the 56-65 age group, and the remainder of the sample represented by 0.9% preferred not to indicate their age.

Table 4-04: Age group of respondents

		Frequency	Percent
Valid	Under 18	10	2.3
	18 - 25	101	23.0
	26 - 35	193	43.9
	36 - 45	104	23.6
	46 - 55	22	5.0
	56 - 65	6	1.4
	Prefer not to say	4	0.9
	Total	440	100.0

Source: Author's calculations

4.4.4 EDUCATION

Table 4-05 shows that 46.4% of the overall sample had a post-graduate degree as their highest education. This was followed by 23.2% having a bachelor's degree, and 21.1% having completed grade 12. Of the remaining sample, 8.0% had completed a diploma and 1.4% preferred not to say.

Table 4-05: Education level of respondents

Education	Count	Percent
Postgraduate degree	204	46.4
Bachelor's degree	102	23.2
Grade 12 completed	93	21.1
Post high school certificate/diploma	35	8.0
Prefer not to say	6	1.4
Total	440	100.0

Source: Author's calculations

4.4.5 CHATBOT USAGE

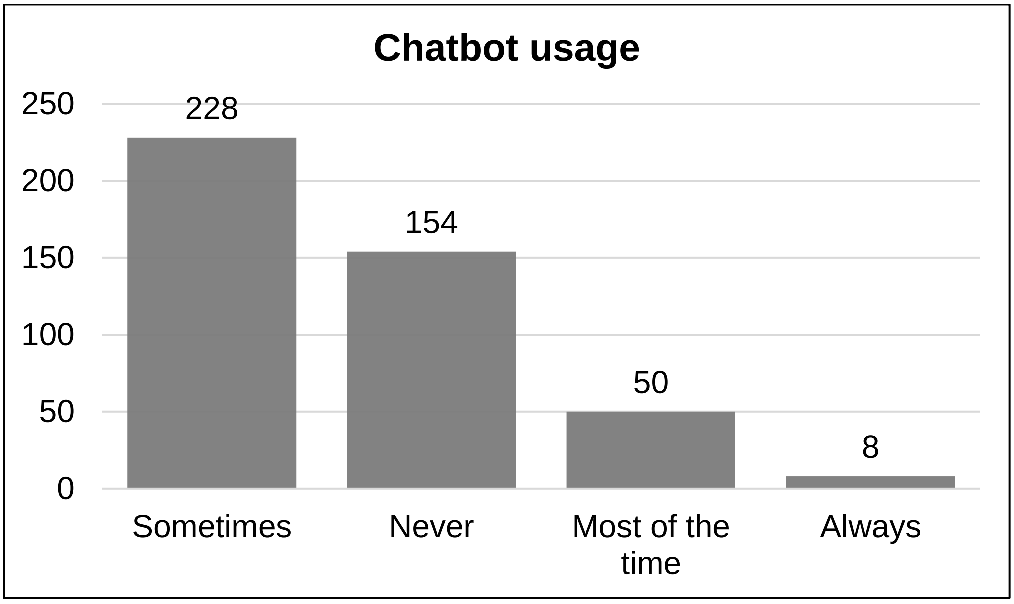
Of the 440 respondents, Figure 3 and Table 4-06 shows that 35% (154) of the respondents never use chatbots to resolve their queries in the financial services industry. However, a little over half of the total respondents (228) sometimes use chatbots and only 2% always use chatbots to resolve their queries.

Table 4-06: Chatbot usage of respondents

		Frequency	Percent
Valid	Sometimes	228	51.8
	Never	154	35.0
	Most of the time	50	11.4
	Always	8	1.8
	Total	440	100.0

Source: Author's calculations

Figure 3: Chatbot usage frequency



When considering chatbot usage per age group, Table 4-07 shows that 102 respondents who fall within the youth (aged 18 - 35) never use chatbots to resolve their queries in the financial services industry, while only 2 respondents in the elderly age group (aged 36 – 65) indicated to always use chatbots.

Table 4-07: Age and chatbot usage cross tabulation

		Chatbot usage				
		Never	Sometimes	Most of the time	Always	Total
Age	Under 18	3	6	1	0	10
	18 - 25	40	51	10	0	101
	26 - 35	62	105	20	6	193
	36 - 45	38	49	15	2	104
	46 - 55	7	12	3	0	22
	56 - 65	3	3	0	0	6
	Prefer not to say	1	2	1	0	4
Total		154	228	50	8	440

Source: Author's calculations

Chatbot usage per gender is represented in Table 4-08. Of the total sample, 78 of the 244 females (approximately 32% of the sample) indicated that they never use chatbots to resolve their queries in the financial services industry, while 69 of the 184 males (approximately 38%) also indicated that they never use chatbots. Only 4 males and 4 females, representing approximately 2% for either gender groups, indicated to always use chatbots.

Table 4-08: Gender and chatbot usage cross tabulation

		Chatbot_usage				
		Never	Sometimes	Most of the time	Always	Total
Gender	Male	69	92	19	4	184
	Female	78	132	30	4	244
	Non-binary / third gender	1	0	0	0	1
	Prefer not to say	6	4	1	0	11
Total		154	228	50	8	440

Source: Author's calculations

4.5 INTERNAL VALIDITY TESTS

Exploratory factor analysis (EFA) was conducted on SPSS to test for internal validity of the research measurement items. The main advantage of EFA in this research was that it reduced the data set collected to a manageable size, while also retaining as much of the original data collected as possible (Field, 2018). Additionally, EFA assisted in determining if there were any multicollinearity problems to prevent a situation where two or more variables are very closely linearly related (Field, 2018).

The factor method used for this research is Principal Axis Factoring, which means that conclusions made in this study are restricted to the sample collected (Field, 2018). The criteria used for extraction was eigenvalue greater than 1. The eigenvalue indicated the importance of a factor, and the value of 1 is informed by Kaiser's criterion (Kaiser, 1960, 1970) which is also the default in SPSS.

This section starts of by presenting the EFA results for the measurement items per construct, and then briefly presents the overall EFA result for all constructs in the research model. It was more valuable to conduct EFA per construct to ensure that all constructs in the conceptual framework are included in the data analysis.

This section presents the factor loadings for the measurement items per construct, followed by the total variance explained in the measurement items, and then the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and the Bartlett's Test of Sphericity. The determinant is also highlighted to detect multicollinearity. If the determinant is great than 0.00001 then it indicates no multicollinearity issues.

The KMO is a measure of the ratio of the squared correlation between the measurement items to the squared partial correlation between the measurement items (Field, 2018). The KMO measure varies between 0 and 1, where a value of 0 indicates a diffusion in the pattern of correlations, signifying that factor analysis is likely to be inappropriate, whereas a value close to 1 indicates that factor analysis would yield distinct and reliable factors (Field, 2018). Values between 0.5 and 0.7 are mediocre but acceptable, and values above 0.7 are great (Field, 2018). For this study, KMO values greater than 0.5 were accepted. On the other hand, Bartlett's test of sphericity provides a measure of the variance-covariance matrix of the measurement items (Field, 2018).

4.5.1 BI

Table 4-09 shows that BI was measured with a total of four items, and all were retained after the principal axis factoring analysis. The criteria for EFA were eigenvalue greater than one, and coefficients (factor loadings) values more than 0.4. All four items were retained in this factor. There was no rotation as only one factor was extracted.

Table 4-09: Factor matrix (BI)

Factor Matrix[a]	
	Factor
	1
BehIntent_1	0.864
BehIntent_2	0.905
BehIntent_3	0.813
BehIntent_4	0.867

Extraction Method: Principal Axis Factoring.
a. 1 factors extracted. 6 iterations required.

Source: Author’s calculations

The results in Table 4-10 show that the one factor extracted explained 80.76% of the variance before extraction, and 74.45% after extraction which is excellent. The determinant returned for this factor was 0.050>0.00001 and therefore no issues of multicollinearity exist for this factor.

Table 4-10: Total variance explained (BI)

Total Variance Explained						
Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.230	80.761	**80.761**	2.978	74.452	74.452
2	0.337	8.416	89.177			
3	0.251	6.271	95.448			
4	0.182	4.552	100.000			
Extraction Method: Principal Axis Factoring.						

Source: Author’s calculations

Table 4-11 shows that the KMO measure of sampling adequacy was greater than the acceptable 0.5, as it measured at 0.839 (Field, 2018). Based on Bartlett’s test of sphericity, Approx. Chi-Square = 1302.557, df = 6, indicating that the correlation between the measurement items for BI is large enough and significant for factor analysis. Therefore, this factor was accepted.

Table 4-11: KMO and Bartlett’s test (BI)

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.839
Bartlett's Test of Sphericity	Approx. Chi-Square	1302.557
	df	6
	Sig.	<0,001

Source: Author’s calculations

4.5.2 FC

FC was measured with a total of four items as presented in Table 4-11 and all were retained after EFA. The extraction method used was principal axis factoring. The criteria for EFA were an eigenvalue greater than one and coefficients value more than 0.4 was applied. There was no rotation as only one factor was extracted.

Table 4-11: Factor matrix (FC)

Factor Matrix	
	Factor
	1
FcCndn_1	0.678
FcCndn_2	0.826
FcCndn_3	0.734
FcCndn_4	0.436
Extraction Method: Principal Axis Factoring.	
a. 1 factors extracted. 10 iterations are required.	

Source: Author’s calculations

The results in Table 4-12 show that the one factor extracted explained 58.67% of the variance.

Table 4-12: Total variance explained (FC)

Total Variance Explained						
	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.347	58.676	**58.676**	1.871	46.764	46.764
2	0.822	20.543	79.219			
3	0.484	12.092	91.311			
4	0.348	8.689	100.000			
Extraction Method: Principal Axis Factoring.						

Source: Author’s calculations

Table 4-13 shows that the KMO measure of sampling adequacy was greater than the acceptable 0.5, as it measured at 0.718 (Field, 2018). Bartlett's test of sphericity, Approx. Chi-Square = 490.915, df = 3, indicated that the correlation between the measurement items for FC is large enough and significant for factor analysis. Additionally, the determinant of 0.342>0.00001 suggested that there are no multicollinearity issues. This factor was therefore accepted.

Table 4-13: KMO and Bartlett's test (FC)

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.718
Bartlett's Test of Sphericity	Approx. Chi-Square	490.915
	df	6
	Sig.	<0,001

Source: Author's calculations

4.5.3 ATT

ATT was measured with four items as shown in Table 4-14 and all for were retained after EFA as they had coefficient values more than 0.4. The criteria for EFA were eigenvalue greater than one and coefficient values more than 0.4.

Table 4-14: Factor matrix (ATT)

Factor Matrix[a]	
	Factor
	1
ATT_1	0.862
ATT_2	0.891
ATT_3	0.884
ATT_4	0.870
Extraction Method: Principal Axis Factoring.	
a. 1 factors extracted. 5 iterations required.	

Source: Author's calculations

Table 4-15 presents that one factor was extracted with an eigenvalue of 3.305, and it explained 82.62% of the varianbefore to extraction which is considered excellent. Therefore, this factor was accepted. The determinant of 0.038>0.00001 also indicated that there is no multicollinearity matters to be addressed.

Table 4-15: Total variance explained (ATT)

Total Variance Explained						
	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.305	82.621	**82.621**	3.073	76.836	76.836
2	0.308	7.696	90.317			
3	0.196	4.902	95.219			
4	0.191	4.781	100.000			
Extraction Method: Principal Axis Factoring.						

Source: Author's calculations

Table 4-16 shows that the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was greater than the acceptable 0.5, as it measured at 0.845 (Field, 2018). Based on Bartlett's test of sphericity, Approx. Chi-Square = 1426.813, df = 6, indicating that the correlation between the measurement items for ATT is large enough and significant for factor analysis.

Table 4-16: KMO and Bartlett's test (ATT)

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.845
Bartlett's Test of Sphericity	Approx. Chi-Square	1426.813
	df	6
	Sig.	<0,001

Source: Author's calculations

4.5.4 PR

The PR construct was measured using seven measurement items altogether, with four measuring performance risk, and three measuring privacy risk. The first EFA performed, using the principal axis factoring method, had three measurement items loading negatively and two measurement items with cross loadings, which were removed as this indicated a poor relationship with the other measurement items in the PR construct. Additionally, the first EFA returned two factors for this construct whereas only one was desired.

After removing the negatively loading measurement items, EFA was performed again, and still using principal axis factoring. The results in Table 4-17 show that the two blank measurement items were below the coefficient criterion of greater than 0.4 applied in this study, these were therefore removed from the factor, which left only two measurement items for the PR construct. Ideally, three measurement items should be present for every factor to be accepted, however, this factor was cautiously accepted because the factor loadings were greater than 0.7. Accepting these two factor loadings also enabled the inclusion of the PR factor into the data analysis.

Table 4-17: Factor matrix (PR)

Factor Matrix[a]	
	Factor
	1
PrvcyRisk_2	0.752
PrvcyRisk_3	0.850
PerfRisk_3	
PerfRisk_4	
Extraction Method: Principal Axis Factoring.	
a. 1 factors extracted. 20 iterations required.	

Source: Author's calculations

Table 4-18 presents that one factor was extracted with eigenvalue of 1.912, and it explained only 47.8% of the variance. Although this variance is poor, the factor was accepted because of the variance being close to 50%, and so that PR can be included in the data analysis. Accepting this factor meant that all hypotheses affected or affecting PR had to be cautiously interpreted as the low variance indicated that this factor was not strong enough in the overall conceptual model.

Table 4-18: Total variance explained (PR)

Total Variance Explained						
Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.912	47.796	**47.796**	1.467	36.675	36.675
2	0.976	24.397	72.193			
3	0.765	19.119	91.312			
4	0.348	8.688	100.000			
Extraction Method: Principal Axis Factoring.						

Source: Author's calculations

Table 4-19 shows that the KMO measure of sampling adequacy was greater than the acceptable 0.5, as it measured at 0.597 (Field, 2018). Based on Bartlett's test of sphericity, Approx. Chi-Square = 305.013, df = 6, indicating that the correlation between the measurement items for PR is large and significant for factor analysis. This factor was therefore accepted, albeit cautiously.

Table 4-19: KMO and Bartlett's test (PR)

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.597
Bartlett's Test of Sphericity	Approx. Chi-Square	305.013
	df	6
	Sig.	<0,001

Source: Author's calculations

4.5.5 EE

Four items were used to measure EE and all four were retained after EFA as seen in Table 4-20. All four items returned factor loadings of greater than 0.4.

Table 4-20: Factor matrix (EE)

Factor Matrix[a]	
	Factor
	1
EffExp_1	0.728

EffExp_2	0.684
EffExp_3	0.762
EffExp_4	0.812
Extraction Method: Principal Axis Factoring.	
a. 1 factors extracted. 7 iterations required.	

Source: Author's calculations

The criteria for EFA were eigenvalue greater than one. Table 4-21 presents that one factor was extracted with eigenvalue of 2.673, and it explained 66.81% of the variance which is considered good. Additionally, the determinant of 0.223>0.00001 indicated that there were no issues of multicollinearity. Therefore, this factor was accepted.

Table 4-21: Total variance explained (EE)

Total Variance Explained						
Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.673	66.814	**66.814**	2.239	55.966	55.966
2	0.519	12.979	79.793			
3	0.458	11.448	91.240			
4	0.350	8.760	100.000			
Extraction Method: Principal Axis Factoring.						

Source: Author's calculations

Table 4-22 shows that the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was greater than the acceptable 0.5, as it measured at 0.805 (Field, 2018). Based on Bartlett's test of sphericity, Approx. Chi-Square = 650.272, df = 6, indicating that the correlation between the measurement items for EE is large enough and significant for factor analysis.

Table 4-22: KMO and Bartlett's test (EE)

KMO and Bartlett's Test	
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.	0.805

Bartlett's Test of Sphericity	Approx. Chi-Square	650.272
	df	6
	Sig.	<0,001

Source: Author's calculations

4.5.6 UPE

UPE was measured with a total of four items as presented in Table 4-23 and all were retained after EFA as all four returned coefficients of greater than 0.4. The criteria for EFA were eigenvalue greater than one and coefficients value more than 0.4 was applied. The principal axis factoring method was used for factor analysis. There was no rotation as only one factor was extracted.

Table 4-23: Factor matrix (UPE)

Factor Matrix[a]	
	Factor
	1
UtlPerfExp_1	0.811
UtlPerfExp_2	0.888
UtlPerfExp_3	0.877
UtlPerfExp_4	0.807
Extraction Method: Principal Axis Factoring.	
a. 1 factors extracted. 6 iterations required.	

Source: Author's calculations

Table 4-24 shows that the one factor that was extracted for UPE had an eigenvalue of 3.146 and explained 78.66% of the variance prior to extraction, which is considered excellent. This factor was therefore retained for analysis.

Table 4-24: Total variance explained (UPE)

Total Variance Explained						
	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.146	78.656	**78.656**	2.867	71.675	71.675
2	0.363	9.071	87.727			
3	0.269	6.724	94.451			
4	0.222	5.549	100.000			
Extraction Method: Principal Axis Factoring.						

Source: Author's calculations

Table 4-25 shows that the KMO measure of sampling adequacy was greater than the acceptable 0.5, as it measured at 0.846 (Field, 2018). Based on Bartlett's test of sphericity, Approx. Chi-Square = 1162.59, df = 6, indicating that the correlation between the measurement items for UPE is large enough and significant for factor analysis. This factor was therefore accepted.

Table 4-25: KMO and Bartlett's test (UPE)

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.846
Bartlett's Test of Sphericity	Approx. Chi-Square	1162.595
	df	6
	Sig.	<0,001

Source: Author's calculations

4.5.7 PS

PS was measured by four items in the research instrument. EFA initially returned a negative coefficient for one measurement item, and it had to be removed. The second EFA then returned positive coefficients of greater than 0.4 as presented in Table 4-26 and only three measurement items were retained in the data set.

Table 4-26: Factor matrix (PS)

Factor Matrix[a]	
	Factor
	1
Security_1	0.673
Security_3	0.804
Security_4	0.929
Extraction Method: Principal Axis Factoring.	
a. 1 factors extracted. 15 iterations required.	

Source: Author's calculations

Table 4-27 shows that the one factor that was extracted for PS had an eigenvalue of 2.279 and explained 75.96% of the variance prior to extraction, which is considered good. This factor was therefore accepted and retained for analysis.

Table 4-27: Total variance explained (PS)

Total Variance Explained						
	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.279	75.963	**75.963**	1.962	65.388	65.388
2	0.480	16.003	91.967			
3	0.241	8.033	100.000			
Extraction Method: Principal Axis Factoring.						

Source: Author's calculations

Table 4-28 shows that the KMO measure of sampling adequacy was greater than the acceptable 0.5, as it measured at 0.687 (Field, 2018). Based on Bartlett's test of sphericity, Approx. Chi-Square = 580.095, df = 3, indicating that the correlation between the measurement items for PS is large enough and significant for factor analysis.

Table 4-28: KMO and Bartlett's test (PS)

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.687
Bartlett's Test of Sphericity	Approx. Chi-Square	580.095
	df	3
	Sig.	<0,001

Source: Author's calculations

4.5.8 SE

Table 4-29 shows that SE was measured using four items which all returned coefficients greater than 0.4 and were therefore retained.

Table 4-29: Factor matrix (Self Efficacy)

Factor Matrix[a]	
	Factor
	1
SlfEffcy_1	0.490
SlfEffcy_2	0.523
SlfEffcy_3	0.793
SlfEffcy_4	0.754
Extraction Method: Principal Axis Factoring.	
a. 1 factors extracted. 10 iterations required.	

Source: Author's calculations

The factor analysis criteria was eigenvalue greater than 1. Table 4-30 shows that the one factor that was extracted for SE had an eigenvalue of 2.236 and explained 55.9% of the variance prior to extraction which is acceptable. The factor was therefore accepted.

Table 4-30: Total variance explained (SE)

Total Variance Explained						
Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.236	55.900	**55.900**	1.711	42.779	42.779
2	1.091	27.275	83.176			
3	0.428	10.708	93.884			
4	0.245	6.116	100.000			
Extraction Method: Principal Axis Factoring.						

Source: Author's calculations

Table 4-31 shows that the KMO measure of sampling adequacy was greater than the acceptable 0.5, as it measured at 0.576 (Field, 2018). Based on Bartlett's test of sphericity, Approx. Chi-Square = 593.120, df = 6, indicating that the correlation between the measurement items for SE is large enough and significant for factor analysis. This factor was therefore accepted.

Table 4-31: KMO and Bartlett's test (SE)

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.576
Bartlett's Test of Sphericity	Approx. Chi-Square	593.120
	df	6
	Sig.	<0,001

Source: Author's calculations

4.5.9 PT

PT was measured with four items as shown in Table 4-32 and all for were retained after EFA as they had factor loading values more than 0.4.

Table 4-32: Factor matrix (PT)

Factor Matrix[a]	
	Factor
	1
Trust_1	0.802

Trust_2	0.779
Trust_3	0.836
Trust_4	0.682
Extraction Method: Principal Axis Factoring.	
a. 1 factors extracted. 6 iterations required.	

Source: Author's calculations

The criteria for EFA were eigenvalue greater than 1, applying Kaiser's criterion. Table 4-33 presents that one factor was extracted with an eigenvalue of 2.802, and it explained 70.06% of the variance before extraction, which is considered good, and therefore, this factor was accepted. Additionally, the determinant of 0.169>0.00001 shows that there is no multicollinearity matters to be addressed.

Table 4-33: Total variance explained (PT)

Total Variance Explained						
	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.802	70.055	**70.055**	2.415	60.386	60.386
2	0.502	12.549	82.604			
3	0.372	9.305	91.909			
4	0.324	8.091	100.000			
Extraction Method: Principal Axis Factoring.						

Source: Author's calculations

Table 4-34 shows that the KMO measure of sampling adequacy was greater than the acceptable 0.5, as it measured at 0.822 (Field, 2018). Based on Bartlett's test of sphericity, Approx. Chi-Square = 773.713, df = 6, indicating that the correlation between the measurement items for PT is large enough and significant for factor analysis. As such, this factor was accepted.

Table 4-34: KMO and Bartlett's test (PT)

KMO and Bartlett's Test	
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.	0.822

Bartlett's Test of Sphericity	Approx. Chi-Square	773.713
	df	6
	Sig.	<0,001

Source: Author's calculations

4.5.10 SI

The SI construct was measured with four measurement items and Table 4-35 presents a positive coefficient of greater than 0.4 for all four items.

Table 4-35: Factor matrix (SI)

Factor Matrix[a]	
	Factor
	1
SocialInflnce_1	0.833
SocialInflnce_2	0.937
SocialInflnce_3	0.848
SocialInflnce_4	0.924
Extraction Method: Principal Axis Factoring.	
a. 1 factors extracted. 6 iterations required.	

Source: Author's calculations

The criteria for EFA was an eigenvalue greater than 1. Table 4-36 presents that one factor was extracted with an eigenvalue of 3.353, and it explained 83.83% of the varbeforeior to extraction, which is considered excellent, and therefore, this factor was accepted. Additionally, the determinant of 0.029>0.00001 indicates that there is no multicollinearity matters to be addressed for this construct.

Table 4-36: Total variance explained (SI)

Total Variance Explained						
Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.353	83.833	**83.833**	3.146	78.648	78.648
2	0.310	7.743	91.576			
3	0.193	4.817	96.393			
4	0.144	3.607	100.000			
Extraction Method: Principal Axis Factoring.						

Source: Author's calculations

Table 4-37 shows that the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was greater than the acceptable 0.5, as it measured at 0.857 (Field, 2018). Based on Bartlett's test of sphericity, Approx. Chi-Square = 1534.308, df = 6, indicating that the correlation between the measurement items for SI is large enough and significant for factor analysis.

Table 4-37: KMO and Bartlett's test (SI)

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.857
Bartlett's Test of Sphericity	Approx. Chi-Square	1534.308
	df	6
	Sig.	0.000

Source: Author's calculations

4.5.11 HPE

The HPE construct was measured using three items and all returned factor loadings greater than 0.4 as shown in Table 4-38.

Table 4-38: Factor matrix (HPE)

Factor Matrix[a]	
	Factor
	1
HedPerfExp_1	0.931

HedPerfExp_2	0.964
HedPerfExp_3	0.848
Extraction Method: Principal Axis Factoring.	
a. 1 factors extracted. 8 iterations required.	

Source: Author's calculations

The criteria for EFA was an eigenvalue greater than 1. Table 4-39 presents that one factor was extracted wian th eigenvalue of 2.671, and it explained 89.02% of the varbeforeior to extraction, which is considered excellent, and therefore, this factor was accepted. Additionally, the determinant of 0.061>0.00001 shows that there is no multicollinearity matters to be addressed for the HPE construct.

Table 4-39: Total variance explained (HPE)

Total Variance Explained						
	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.671	89.024	**89.024**	2.515	83.849	83.849
2	0.230	7.671	96.694			
3	0.099	3.306	100.000			
Extraction Method: Principal Axis Factoring.						

Source: Author's calculations

Table 4-40 shows that the KMO measure of sampling adequacy was greater than the acceptable 0.5, as it measured at 0.744 (Field, 2018). Based on Bartlett's test of sphericity, Approx. Chi-Square = 1217.480, df = 3, indicating that the correlation between the measurement items for HPE is large enough and significant for factor analysis. This factor was therefore accepted.

Table 4-40: KMO and Bartlett's test (HPE)

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.744
Bartlett's Test of Sphericity	Approx. Chi-Square	1217.480
	df	3
	Sig.	<0,001

Source: Author's calculations

4.5.12 OVERALL MEASUREMENT MODEL

Overall, the conceptual framework in this study consisted of 11 constructs – BI, FC, ATT, PR, EE, UPE, PS, SE, PT, SI, and HPE.

After running EFA using the principal axis factoring method for all the constructs separately, the EFA result was extracted for all the measurement items in the research model. SPSS was instructed to extract 11 constructs. The factor matrix is presented in Appendix F and clearly shows that some factors had negative loadings, and more importantly, all factors loaded across all 11 constructs, further proving that EFA was more meaningful when performed per construct as in the above section.

Table 4-41 presents the overall KMO and Bartlett's test results for the measurement model. The KMO measure of sampling adequacy for the overall research model is 0.931, indicating that the sample size and the set of variables were adequate for data analysis. The KMO measure verified the sampling adequacy for the analysis.

Table 4-41: KMO and Bartlett's Test (overall research model)

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.931
Bartlett's Test of Sphericity	Approx. Chi-Square	13355.293
	df	1035
	Sig.	0.000

Source: Author's calculations

4.5.13 SUMMARY OF INTERNAL VALIDITY TESTS AND EXPLORATORY FACTOR ANALYSIS

Of all the 46 measurement items (Appendix D) in the research instrument, 40 items remained after EFA was performed as presented in Table 4-42. All the factors had three or more measurement items, except for PR which only had two. Therefore, the hypotheses affected by or affecting PR were cautiously interpreted during the data analysis.

Table 4-42: EFA integrated results

Item	1	2	3	4	5	6	7	8	9	10	11
BehIntent_1	0.864										
BehIntent_2	0.905										
BehIntent_3	0.813										
BehIntent_4	0.867										
FcCndn_1		0.678									
FcCndn_2		0.826									
FcCndn_3		0.734									
FcCndn_4		0.436									
ATT_1			0.862								
ATT_2			0.891								
ATT_3			0.884								
ATT_4			0.870								
PrvcyRisk_2				0.752							
PrvcyRisk_3				0.850							
EffExp_1					0.728						
EffExp_2					0.684						
EffExp_3					0.762						
EffExp_4					0.812						
UtlPerfExp_1						0.811					
UtlPerfExp_2						0.888					
UtlPerfExp_3						0.877					
UtlPerfExp_4						0.807					
Security_1							0.673				
Security_3							0.804				
Security_4							0.929				
SlfEffcy_1								0.490			
SlfEffcy_2								0.523			
SlfEffcy_3								0.793			
SlfEffcy_4								0.754			
Trust_1									0.802		
Trust_2									0.779		
Trust_3									0.836		
Trust_4									0.682		
SocialInflnce_1										0.833	
SocialInflnce_2										0.937	
SocialInflnce_3										0.848	
SocialInflnce_4										0.924	
HedPerfExp_1											0.931
HedPerfExp_2											0.964
HedPerfExp_3											0.848

Source: Author's calculations

Note: BehIntent = Behavioural Intent, FcCndn = FC, PrvcyRisk = Privacy Risk, EfftExp = EE, UtlPerfExp = UPE, SlfEffcy = SE, SocialInflnce = SI, HedPerfExp = HPE

4.6 INTERNAL CONSISTENCY

Internal consistency of the research constructs was measured by assessing the Cronbach α per construct. Reliability analysis was performed on SPSS and SPSS was instructed to return the Cronbach α for the items per factor identified in EFA above, the Cronbach α value when an item is deleted, as well as the correlation between all the measurement items per factor that is presented in the EFA integrated results.

Internal consistency was assessed per factor identified in EFA and this section presents the results. The criteria for Cronbach α is 0.7 and above, which is considered good. If this criterion is met, then the scales are deemed to be reliable, and it is confirmed that internal consistency exists in the measurement items, therefore supporting the acceptance of the factor into the data analysis process.

4.6.1 FACTOR 1: BI

The overall reliability of the BI factor presented in Table 4-43 is 0.920, which indicates good reliability.

Table 4- 43: Reliability statistics (BI)

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0.920	0.920	4

Source: Author's calculations

The Inter-Item correlation matrix in Table 4-44 indicates that the correlations between the measurement items for the BI scale were all above 0.3 which is good, and therefore acceptable.

Table 4-44: Inter-item correlation matrix (BI)

Inter-Item Correlation Matrix				
	BehIntent_1	BehIntent_2	BehIntent_3	BehIntent_4
BehIntent_1	1.000			

BehIntent_2	0.803	1.000		
BehIntent_3	0.672	0.741	1.000	
BehIntent_4	0.755	0.758	0.729	1.000

Source: Author's calculations

Table 4-45 shows that the Corrected Item-Total Correlations are all above 0.3 which is good as it means that all the items correlate well with the BI scale overall. Items below 0.3 would have to be dropped (Field, 2018). Additionally, Cronbach's α would not increase if any items were deleted.

Table 4-45: Item-total statistics (BI)

Item-Total Statistics					
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
BehIntent_1	7.83	5.390	0.817	0.697	0.896
BehIntent_2	7.92	5.191	0.851	0.734	0.884
BehIntent_3	8.14	5.385	0.776	0.616	0.910
BehIntent_4	8.01	5.149	0.822	0.677	0.894

Source: Author's calculations

4.6.2 FACTOR 2: FC

The overall reliability of the FC factor presented in Table 4-46 is 0.757, which indicates good scale reliability.

Table 4- 46: Reliability statistics (FC)

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0.757	0.759	4

Source: Author's calculations

The Inter-Item correlation matrix in Table 4-47 indicates that the correlations between the measurement items for the FC scale were all above 0.3 which is good, and therefore acceptable.

Table 4-47: Inter-item correlation matrix (FC)

Inter-Item Correlation Matrix				
	FcCndn_1	FcCndn_2	FcCndn_3	FcCndn_4
FcCndn_1	1.000			
FcCndn_2	0.619	1.000		
FcCndn_3	0.462	0.581	1.000	
FcCndn_4	0.244	0.311	0.423	1.000

Source: Author's calculations

Table 4-48 shows that the Corrected Item-Total Correlations are all above 0.3 which is good as it means that all the items correlate well with the FC scale overall. Items below 0.3 would have to be dropped (Field, 2018). Additionally, the table shows that Cronbach's α would increase slightly to 0.789 if the FcCndn_4 item was deleted. This item was however not deleted as the overall α was still acceptable.

Table 4-48: Item-total statistics (FC)

Item-Total Statistics					
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
FcCndn_1	9.02	3.783	0.559	0.399	0.697
FcCndn_2	9.29	3.366	0.654	0.496	0.641
FcCndn_3	9.43	3.634	0.635	0.415	0.657
FcCndn_4	9.62	4.095	0.387	0.186	0.789

Source: Author's calculations

4.6.3 FACTOR 3: ATT

The overall reliability of the ATT factor presented in Table 4-49 is 0.930, which indicates good scale reliability.

Table 4- 49: Reliability statistics (ATT)

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0.930	0.930	4

Source: Author's calculations

The Inter-Item correlation matrix in Table 4-50 indicates that the correlations between the measurement items for the ATT scale were all above 0.3 which is good, and therefore acceptable.

Table 4-50: Inter-item correlation matrix (ATT)

Inter-Item Correlation Matrix				
	ATT_1	ATT_2	ATT_3	ATT_4
ATT_1	1.000			
ATT_2	0.804	1.000		
ATT_3	0.745	0.768	1.000	
ATT_4	0.728	0.759	0.804	1.000

Source: Author's calculations

Table 4-51 shows that the Corrected Item-Total Correlations are all above 0.3 which is good as it means that all the items correlate well with the ATT scale overall. Items below 0.3 would have to be dropped (Field, 2018).

Table 4-51: Item-total statistics (ATT)

Item-Total Statistics					
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
ATT_1	8.25	5.395	0.822	0.694	0.913
ATT_2	8.19	5.426	0.848	0.728	0.904
ATT_3	8.24	5.320	0.842	0.719	0.906
ATT_4	8.33	5.401	0.830	0.704	0.910

Source: Author's calculations

4.6.4 FACTOR 4: PR

The overall reliability of the PR factor presented in Table 4-52 is 0.788, which indicates good scale reliability.

Table 4- 52: Reliability statistics (PR)

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0.788	0.788	2

Source: Author’s calculations

The Inter-Item correlation matrix in Table 4-53 indicates that the correlations between the measurement items for the PR scale were both above 0.3 which is good and therefore acceptable.

Table 4-53: Inter-item correlation matrix (PR)

Inter-Item Correlation Matrix		
	PrvcyRisk_2	PrvcyRisk_3
PrvcyRisk_2	1.000	
PrvcyRisk_3	0.651	1.000

Source: Author’s calculations

Table 4-54 shows that the Corrected Item-Total Correlations are both above 0.3 which is good as it means that all the items correlate well with the PR scale overall. Items below 0.3 would have to be dropped (Field, 2018).

Table 4-54: Item-total statistics (PR)

Item-Total Statistics					
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
PrvcyRisk_2	2.55	0.646	0.651	0.423	.
PrvcyRisk_3	2.72	0.643	0.651	0.423	.

Source: Author’s calculations

4.6.5 FACTOR 5: EE

The overall reliability of the EE factor presented in Table 4-55 is 0.833, which indicates good scale reliability.

Table 4- 55: Reliability statistics (EE)

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0.833	0.834	4

Source: Author’s calculations

The Inter-Item correlation matrix in Table 4-56 indicates that the correlations between the measurement items for the EE scale were all above 0.3 which is good, and therefore acceptable.

Table 4-56: Inter-item correlation matrix (EE)

Inter-Item Correlation Matrix				
	EffExp_1	EffExp_2	EffExp_3	EffExp_4
EffExp_1	1.000			
EffExp_2	0.525	1.000		
EffExp_3	0.556	0.495	1.000	
EffExp_4	0.568	0.557	0.641	1.000

Source: Author’s calculations

Table 4-57 shows that the Corrected Item-Total Correlations are all above 0.3 which is good as it means that all the items correlate well with the EE scale overall. Items below 0.3 would have to be dropped (Field, 2018).

Table 4-57: Item-total statistics (EE)

Item-Total Statistics					
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
EffExp_1	9.15	3.125	0.652	0.426	0.794
EffExp_2	9.43	3.147	0.619	0.386	0.809
EffExp_3	9.22	3.205	0.676	0.475	0.785
EffExp_4	9.42	2.805	0.710	0.515	0.768

Source: Author’s calculations

4.6.6 FACTOR 6: UPE

The overall reliability of the UPE factor presented in Table 4-58 is 0.908, which indicates good scale reliability.

Table 4- 58: Reliability statistics (UPE)

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0.908	0.909	4

Source: Author's calculations

The Inter-Item correlation matrix in Table 4-59 indicates that the correlations between the measurement items for the UPE scale were all above 0.3 which is good, and therefore acceptable.

Table 4-59: Inter-item correlation matrix (UPE)

Inter-Item Correlation Matrix				
	UtlPerfExp_1	UtlPerfExp_2	UtlPerfExp_3	UtlPerfExp_4
UtlPerfExp_1	1.000			
UtlPerfExp_2	0.740	1.000		
UtlPerfExp_3	0.701	0.770	1.000	
UtlPerfExp_4	0.644	0.708	0.727	1.000

Source: Author's calculations

Table 4-60 shows that the Corrected Item-Total Correlations are all above 0.3 which is good as it means that all the items correlate well with the UPE scale overall. Items below 0.3 would have to be dropped (Field, 2018).

Table 4-60: Item-total statistics (UPE)

Item-Total Statistics					
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
UtlPerfExp_1	8.45	4.363	0.764	0.599	0.892
UtlPerfExp_2	8.39	4.358	0.829	0.693	0.870

UtlPerfExp_3	8.54	4.166	0.820	0.678	0.872
UtlPerfExp_4	8.36	4.232	0.763	0.592	0.893

Source: Author's calculations

4.6.7 FACTOR 7: PS

The overall reliability of the PS factor presented in Table 4-61 is 0.841, which indicates good scale reliability.

Table 4- 61: Reliability statistics (PS)

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0.841	0.841	3

Source: Author's calculations

The Inter-Item correlation matrix in Table 4-62 indicates that the correlations between the measurement items for the PS scale were all above 0.3 which is good, and therefore acceptable.

Table 4-62: Inter-item correlation matrix (PS)

Inter-Item Correlation Matrix			
	Security_1	Security_3	Security_4
Security_1	1.000		
Security_3	0.540	1.000	
Security_4	0.625	0.747	1.000

Source: Author's calculations

Table 4-63 shows that the Corrected Item-Total Correlations are all above 0.3 which is good as it means that all the items correlate well with the PS scale overall. Items below 0.3 would have to be dropped (Field, 2018).

Table 4-63: Item-total statistics (PS)

Item-Total Statistics					
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Security_1	4.58	2.304	0.622	0.403	0.855
Security_3	4.84	2.010	0.715	0.567	0.769
Security_4	4.63	2.004	0.784	0.628	0.700

Source: Author's calculations

4.6.8 FACTOR 8: SE

The overall reliability of the SE factor presented in Table 4-64 is 0.736, which indicates good scale reliability.

Table 4- 64: Reliability statistics (SE)

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0.736	0.736	4

Source: Author's calculations

The Inter-Item correlation matrix in Table 4-65 indicates that some of the correlations between the measurement items for the SE scale below 0.3 which is a concern. However, in conjunction with the Corrected Item-Total Correlations in Table 4-66 being all above 0.3, the measurement items were accepted with caution.

Table 4-65: Inter-item correlation matrix (SE)

Inter-Item Correlation Matrix				
	SlfEffcy_1	SlfEffcy_2	SlfEffcy_3	SlfEffcy_4
SlfEffcy_1	1.000			
SlfEffcy_2	0.586	1.000		
SlfEffcy_3	**0.255**	0.336	1.000	
SlfEffcy_4	**0.281**	**0.262**	0.740	1.000

Source: Author's calculations

Table 4-66: Item-total statistics (SE)

Item-Total Statistics					
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
SlfEffcy_1	8.00	3.682	0.467	0.363	0.710
SlfEffcy_2	7.95	3.521	0.492	0.383	0.697
SlfEffcy_3	8.50	3.230	0.594	0.571	0.637
SlfEffcy_4	8.46	3.215	0.561	0.559	0.657

Source: Author's calculations

4.6.9 FACTOR 9: PT

The overall reliability of the PT factor presented in Table 4-67 is 0.856, which indicates good scale reliability.

Table 4- 67: Reliability statistics (PT)

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0.856	0.857	4

Source: Author's calculations

The Inter-Item correlation matrix in Table 4-68 indicates that the correlations between the measurement items for the PT scale were all above 0.3 which is good, and therefore acceptable.

Table 4-68: Inter-item correlation matrix (PT)

Inter-Item Correlation Matrix				
	Trust_1	Trust_2	Trust_3	Trust_4
Trust_1	1.000			
Trust_2	0.634	1.000		
Trust_3	0.671	0.644	1.000	
Trust_4	0.537	0.532	0.580	1.000

Source: Author's calculations

Table 4-69 shows that the Corrected Item-Total Correlations are all above 0.3 which is good as it means that all the items correlate well with the PT scale overall. Items below 0.3 would have to be dropped (Field, 2018).

Table 4-69: Item-total statistics (PT)

Item-Total Statistics					
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Trust_1	8.08	3.717	0.720	0.534	0.807
Trust_2	7.94	3.773	0.704	0.506	0.814
Trust_3	8.07	3.813	0.749	0.565	0.797
Trust_4	7.88	3.896	0.627	0.397	0.847

Source: Author’s calculations

4.6.10 FACTOR 10: SI

The overall reliability of the SI factor presented in Table 4-70 is 0.935, which indicates good scale reliability.

Table 4- 70: Reliability statistics (SI)

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0.935	0.935	4

Source: Author’s calculations

The Inter-Item correlation matrix in Table 4-71 indicates that the correlations between the measurement items for the SI scale were all above 0.3 which is good, and therefore acceptable.

Table 4-71: Inter-item correlation matrix (SI)

Inter-Item Correlation Matrix				
	SocialInflnce_1	SocialInflnce_2	SocialInflnce_3	SocialInflnce_4
SocialInflnce_1	1.000			
SocialInflnce_2	0.786	1.000		

SocialInflnce_3	0.691	0.804	1.000	
SocialInflnce_4	0.779	0.854	0.789	1.000

Source: Author's calculations

Table 4-72 shows that the Corrected Item-Total Correlations are all above 0.3 which is good as it means that all the items correlate well with the SI scale overall. Items below 0.3 would have to be dropped (Field, 2018).

Table 4-72: Item-total statistics (SI)

Item-Total Statistics					
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
SocialInflnce_1	6.78	4.649	0.802	0.661	0.929
SocialInflnce_2	6.79	4.554	0.891	0.798	0.901
SocialInflnce_3	6.73	4.578	0.815	0.686	0.925
SocialInflnce_4	6.76	4.380	0.880	0.781	0.904

Source: Author's calculations

4.6.11 FACTOR 11: HPE

The overall reliability of the HPE factor presented in Table 4-73 is 0.938, which indicates good scale reliability.

Table 4- 73: Reliability statistics (HPE)

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0.938	0.938	3

Source: Author's calculations

The Inter-Item correlation matrix in Table 4-74 indicates that the correlations between the measurement items for the HPE scale were all above 0.3 which is good, and therefore acceptable.

Table 4-74: Inter-item correlation matrix (HPE)

Inter-Item Correlation Matrix			
	HedPerfExp_1	HedPerfExp_2	HedPerfExp_3
HedPerfExp_1	1.000		
HedPerfExp_2	0.899	1.000	
HedPerfExp_3	0.789	0.818	1.000

Source: Author's calculations

Table 4-75 shows that the Corrected Item-Total Correlations are all above 0.3 which is good as it means that all the items correlate well with the HPE scale overall. Items below 0.3 would have to be dropped (Field, 2018).

Table 4-75: Item-total statistics (HPE)

Item-Total Statistics					
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
HedPerfExp_1	5.13	2.368	0.884	0.816	0.899
HedPerfExp_2	5.11	2.389	0.907	0.839	0.882
HedPerfExp_3	5.24	2.425	0.824	0.684	0.946

Source: Author's calculations

4.6.12 SUMMARY OF CONSTRUCT RELIABILITY RESULTS

Cronbach's α is an assessment of internal consistency (Muk & Chung, 2014). All the measures in this study demonstrate reliability with α values of .7 and greater. The inter-item correlations also demonstrate the reliability of the research model.

4.7 COMPOSITE SCORES AND ASSUMPTIONS CHECK

After conducting EFA and assessing the reliability of the data, composite scores were created to transform the measurement items into variables. Measurement items per factor analysed in the above section were grouped, and the mean was calculated to create the new variables. The SPSS compute command using the Mean Function was used to create variables. Therefore, the terminology used henceforth will either be variables or construct.

Assumptions check for the data was conducted by assessing the descriptive statistics, outliers, linearity, and multicollinearity before testing the hypotheses in this study. This section presents the results of the assumptions.

4.7.1 DESCRIPTIVE STATISTICS

Table 4-76: Descriptive statistics for all variables

Descriptive Statistics												
		Beh_Int	Fc_Cdns	Attde	Per_Rsk	Eff_Exp	UtlPExp	Per_Sec	Slf_Effy	Per_Trst	Sc_Infl	HedPExp
N	Valid	440	440	440	440	440	440	440	440	440	440	440
	Missing	0	0	0	0	0	0	0	0	0	0	0
Median		2.7500	3.2500	3.0000	2.5000	3.0000	3.0000	2.3333	2.7500	2.7500	2.0000	2.6667
Mode		3.00	3.00	3.00	3.00	3.00	3.00	2.00	3.00	3.00	2.00	3.00
Mean		2.6587	3.1131	2.7506	2.6284	3.1004	2.8119	2.3405	2.7426	2.6648	2.2494	2.5799
Std. Error of Mean		0.03594	0.02944	0.03645	0.03521	0.02704	0.03230	0.03322	0.02809	0.03023	0.03352	0.03632
Std. Deviation		0.75380	0.61758	0.76466	0.73861	0.56723	0.67749	0.69693	0.58922	0.63417	0.70317	0.76189
Variance		0.568	0.381	0.585	0.546	0.322	0.459	0.486	0.347	0.402	0.494	0.580
Skewness		-0.368	-0.791	-0.441	-0.117	-0.638	-0.600	-0.173	-0.217	-0.398	0.170	-0.285
Std. Error of Skewness		0.116	0.116	0.116	0.116	0.116	0.116	0.116	0.116	0.116	0.116	0.116
Kurtosis		-0.062	1.042	-0.248	-0.119	1.473	0.691	-0.465	0.704	0.263	-0.159	-0.218
Std. Error of Kurtosis		0.232	0.232	0.232	0.232	0.232	0.232	0.232	0.232	0.232	0.232	0.232
Minimum		1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Maximum		4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00

Source: Author's calculations

Note: Beh_Int = Behavioural Intent, Fc_Cdns = FC, Attde = ATT, Per_Rsk = PR, Eff_Exp = EE, UtlPExp = UPE, Per_Sec = PS, Slf_Effy = SE, Per_Trst = PT, Sc_Infl = SI, HedPExp = HPE

Table 4-76 outlines the descriptive statistics for the data collected in this research, including the skewness, kurtosis, mean, mode, and standard deviation measures. The table also shows that there is no missing data.

Firstly, the skewness and kurtosis are an indication of the normality of the data. Skewness refers to the degree of symmetry in the data, and kurtosis refers to the degree to which the data points cluster at the ends of the distribution (Field, 2018). Table 4-76 shows that all the skewness values are close to 0, although most are negative and therefore indicating a pile-up of the data on the right (Field, 2018). The skewness values for this data as shown in Table 4-76 are however all considered normal due to their proximity to 0 (Field, 2018).

Positive values of kurtosis indicate a heavy-tailed distribution whereas negative values indicate a light-tailed distribution (Field, 2018). The kurtosis values are mostly quite close to 0, apart from FC and EE being 1.042 and 1.473, respectively. However, overall, the data indicates normally distributed data, and all the skewness and kurtosis values were in the acceptable values of ±1 (Khalilzadeh, Ozturk & Bilgihan, 2017).

The mean is a simple statistic for the centre of the distribution of score and gives a hypothetical estimate of the typical score (Field, 2018). The mean values for the data ranges between 2.2494 (SI) and 3.1131 (FC). However, the mode is a better indication of the most frequently occurring score as it is not hypothetical, unlike the mean. Most respondents selected the Agree option to the statements in the questionnaire, indicated by a score of 3.00 in Table 4-xx. The mode for the PS and SI statements was Disagree, indicated by a score of 2.00. The median ranges between 2.00 (SI) and 3.25 (FC).

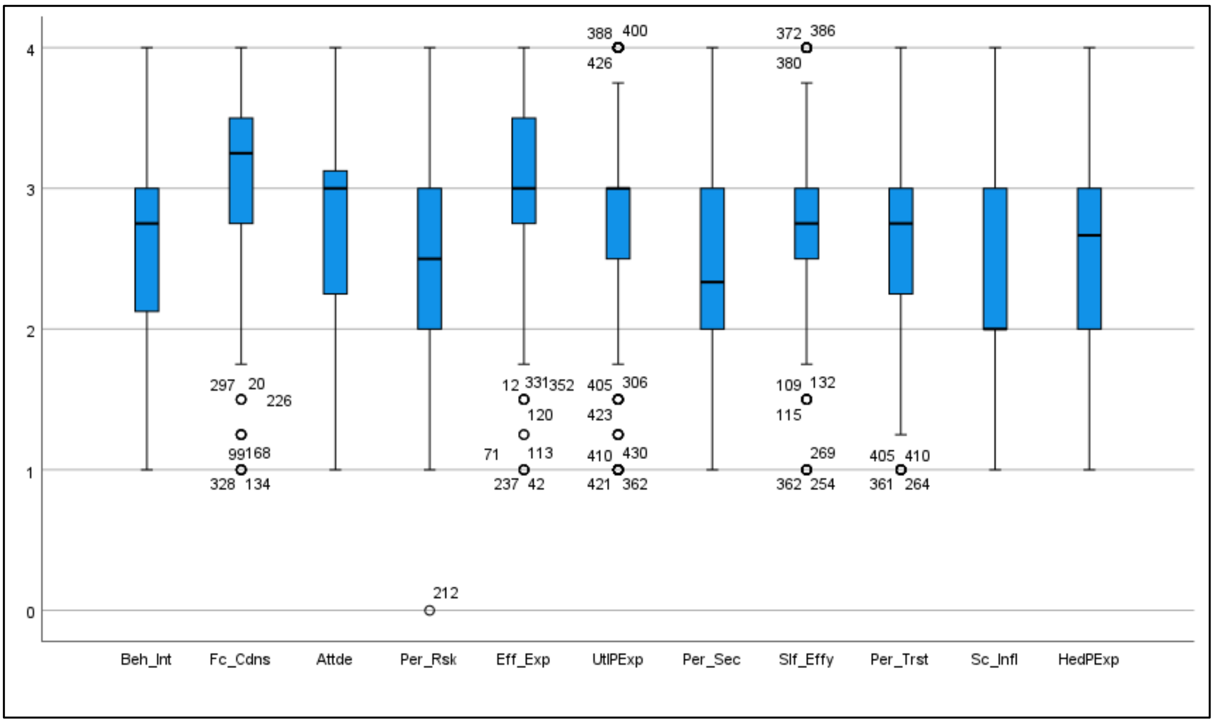
The standard deviations are also presented in Table 4-76. A larger standard deviation relative to the mean suggests that the data is widely spread around the mean, whereas smaller standard deviations relative to the mean suggest that the data is closely packed around the packed (Field, 2018).

Based on the standard deviation, BI (SD = 0.75380), ATT (SD = 0.76466), PR (SD = 0.73861), SI (SD = 0.70317) and HPE (SD = 0.76189), all exhibited the highest standard deviations, indicating a higher variation from the mean for these constructs.

4.7.2 OUTLIERS

To check for bias in the data, an outlier test was conducted. An outlier is a score that is very different from the rest of the data (Field, 2018). The outlier test presented in Figure 4 shows that there are no extreme cases, as those would be represented by an asterisk in the box plot. Although Figure 4 presents no extreme scores, the numbers highlighted in the box plot are mild outliers, however, there is no cause for concern (Field, 2018). As such, there is indication that the data set used in this research is normal.

Figure 4: Outliers test, box plot



Note: Beh_Int = Behavioural Intent, Fc_Cdns = FC, Attde = ATT, Per_Rsk = PR, Eff_Exp = EE, UtlPExp = UPE, Per_Sec = PS, Slf_Effy = SE, Per_Trst = PT, Sc_Infl = SI, HedPExp = HPE

4.7.3 LINEAR CORRELATIONS

The data was tested for multicollinearity by assessing the linear correlations presented in Table 4-77. Multicollinearity issues would exist if two or more variables are very closely linearly related (Field, 2018). The consolidated correlations in Table 4-77 shows that there are no Pearson correlations above 0.9, and if there were, these would indicate a multicollinearity problem (Field, 2018).

Table 4-77: Consolidated correlations of all variables

		Beh_Int	Fc_Cdns	Attde	Per_Rsk	Eff_Exp	UtlPExp	Per_Sec	Slf_Effy	Per_Trst	Sc_Infl	HedPExp
Beh_Int	Pearson Correlation	1										
	Sig. (2-tailed)											
	N	440										
Fc_Cdns	Pearson Correlation	0.141**	1									
	Sig. (2-tailed)	0.003										
	N	440										
Attde	Pearson Correlation	0.718**	0.230**	1								
	Sig. (2-tailed)	<0,001	<0,001									
	N	440										
Per_Rsk	Pearson Correlation	-0.233**	-0.047	-0.230**	1							
	Sig. (2-tailed)	<0,001	0.327	<0,001								
	N	440										
Eff_Exp	Pearson Correlation	0.330**	0.433**	0.332**	-0.145**	1						
	Sig. (2-tailed)	<0,001	<0,001	<0,001	0.002							
	N	440										
UtlPExp	Pearson Correlation	0.727**	0.180**	0.712**	-0.165**	0.340**	1					
	Sig. (2-tailed)	<0,001	<0,001	<0,001	<0,001	<0,001						
	N	440										

		Beh_Int	Fc_Cdns	Attde	Per_Rsk	Eff_Exp	UtlPExp	Per_Sec	Slf_Effy	Per_Trst	Sc_Infl	HedPExp
Per_Sec	Pearson Correlation	0.496**	0.111*	0.467**	-0.510**	0.231**	0.404**	1				
	Sig. (2-tailed)	<0,001	0.020	<0,001	<0,001	<0,001	<0,001					
	N	440										
Slf_Effy	Pearson Correlation	0.269**	-0.027	0.252**	0.016	-0.066	0.288**	0.121*	1			
	Sig. (2-tailed)	<0,001	0.577	<0,001	0.739	0.166	<0,001	0.011				
	N	440										
Per_Trst	Pearson Correlation	0.536**	0.184**	0.551**	-0.329**	0.237**	0.530**	0.532**	0.247**	1		
	Sig. (2-tailed)	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001			
	N	440										
Sc_Infl	Pearson Correlation	0.525**	0.095*	0.459**	-0.122*	0.133**	0.435**	0.410**	0.154**	0.459**	1	
	Sig. (2-tailed)	<0,001	0.047	<0,001	0.010	0.005	<0,001	<0,001	0.001	<0,001		
	N	440										
HedPExp	Pearson Correlation	0.781**	0.093	0.674**	-0.221**	0.280**	0.655**	0.437**	0.294**	0.489**	0.478**	1
	Sig. (2-tailed)	<0,001	0.050	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	
	N	440										

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

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

Source: Author's calculations *(Note: Beh_Int = Behavioural Intent, Fc_Cdns = FC, Attde = ATT, Per_Rsk = PR, Eff_Exp = EE, UtlPExp = UPE, Per_Sec = PS, Slf_Effy = SE, Per_Trst = PT, Sc_Infl = SI, HedPExp = HPE)*

4.8 HYPOTHESIS TESTING

After assessing the statistical assumptions in the above section, this section presents the results per hypothesis. To adequately test the hypotheses outlined in chapter 2, appropriate statistical tests were determined and performed to analyse the data and determine is the hypotheses are supported or rejected.

For H1, H3a, H3b, H4, H5b, H6, H7a, H7b, H7c, H7c, H7d, H7e, H8a, H8b, H8c, H9 – correlation analysis and linear regression was performed. Model Summary statistics were also determined to specifically highlight the R-square value, the Durbin-Watson test statistics, and the significance levels. The R-Square value varies between 0 and 1, and it is an indication of the model's explanatory power and predictive accuracy (Khalilzadeh, Ozturk & Bilgihan, 2017). Pearson correlation coefficient, denoted by r, was calculated to provide the magnitude or direction of the association between two variables (Creswell & Creswell, 2018).

Thirdly, the Analysis of Variance (ANOVA) was determined to test the overall fit of the linear regression models (Field, 2018). The ANOVA and the coefficients are the results of the linear regressions, and they provide an assessment of the predictive capacity of the independent variables on the dependent variable (Msimango-Galawe, 2017).

Additionally, Appendix F presents the histogram and P-P plot (probability-probability plot) for the direct hypotheses and shows that the data used to test these hypotheses look normal as the P-P plot data points fall very close to the diagonal line (Field, 2018).

For the mediation hypotheses – H2a, H2b, H2c, H2d, H3c and H5a - the PROCESS macro in SPSS was used to test these hypotheses.

Multiple regression analysis and squared multiple correlations to determine the R-squared value were also performed to provide details about the relationship between independent variables and dependent variables. Multiple regression analysis was a valuable statistical test because it provided the relative prediction of one variable among many in terms of the outcome of the hypothesis (Creswell & Creswell, 2018).

4.8.1 HYPOTHESIS 1

For this hypothesis, BI is the dependent variable and FC is the independent variable.

Table 4-78 shows that there was a significant positive relationship between FC and BI, $r = .141$, $p < 0.01$. The Pearson correlation of .141 suggests a weak, positive relationship between BI and FC.

Table 4-78: Correlation between FC and BI

Correlations			
		Beh_Int	Fc_Cdns
Pearson Correlation	Beh_Int	1.000	0.141
	Fc_Cdns	0.141	1.000
Sig. (1-tailed)	Beh_Int	.	0.002
	Fc_Cdns	0.002	.
N	Beh_Int	440	440
	Fc_Cdns	440	440

Source: Author's calculations

Note: Fc_Cdns = FC, Beh_Int = BI

The model summary presented in Table 4-79 shows that R-Square = .02, which means that FC associated with chatbots can only account for 2% of the variation in the BI to adopt chatbots in the South African financial services industry. This is a weak result. This means that 98% of the variation in BI to adopt chatbots is unaccounted for in this regression, and this result suggests that other variables in the conceptual framework may have a stronger influence on BI to adopt chatbots.

The Durbin-Watson = 1.87 result indicates that the significance tests for this regression are valid (Field, 2018), additionally, the Durbin-Watson value below 2 indicates a positive correlation between the adjacent residuals.

Table 4-79: Model summary for hypothesis 1

Model Summary[b]					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	0.141[a]	0.020	0.018	0.74712	1.865

a. Predictors: (Constant), Fc_Cdns
b. Dependent Variable: Beh_Int

Source: Author's calculations

Note: Fc_Cdns = FC, Beh_Int = BI

Table 4-80 presents the ANOVA results for this regression. The ANOVA results illustrate that there was a significant effect of FC on BI to adopt chatbots at F(1, 438) = 8.88, p = 0.003.

Table 4-80: ANOVA for hypothesis 1

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4.958	1	4.958	8.882	0.003[b]
	Residual	244.486	438	0.558		
	Total	249.444	439			
a. Dependent Variable: Beh_Int						
b. Predictors: (Constant), Fc_Cdns						

Source: Author's calculations

Note: Fc_Cdns = FC, Beh_Int = BI

The coefficients Table 4-81 presents unstandardised β = .172, p < 0.01 indicating that the FC associated with chatbots are a significant predictor of the BI to adopt chatbots in the South African financial services industry.

The correlation and regression results support the hypothesis that the FC for using chatbots in the South African financial services industry positively affects BI to use chatbots.

Table 4-81: Coefficients for hypothesis 1

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.123	0.183		11.586	<0,001
	Fc_Cdns	0.172	0.058	0.141	2.980	0.003

Source: Author's calculations

Note: Fc_Cdns = FC

4.8.2 HYPOTHESIS 2a

For this mediation hypothesis, ATT (Y) is the dependent variable, EE (X) is the independent variable, and the mediator is HPE (M). Mediation is said to have occurred if the strength of the relationship between the dependent variable and the independent variable is reduced by including the mediator variable (Field, 2018).

Table 4-82 shows that when HPE is not mediating this hypothesis, EE significantly and positively predicts the ATT toward using chatbots, β = .45, 95% CI [0.33, 0.57], t = 7.37, p = .00.

Mediation is tested by assessing the size of the indirect effect of HPE and its confidence interval (CI). Table 4-82 shows that there is a significant indirect effect of EE on ATT towards using chatbots through the HPE from using chatbots, β = .24, 95% CI [0.16, 0.32]. The mediation effect is positive.

If the CI contains zero then we conclude that a mediation effect does not exist, and if the CI does not contain zero then we conclude that a mediation effect exists (Field, 2018). Therefore, the mediation results support the hypothesis that HPE from using chatbots in the South African financial services industry positively mediates the effect of EE on ATT toward using chatbots.

Table 4-82: Total, direct, and indirect effects (Hypothesis 2a)

TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y						
Total effect of X on Y						
Effect	se	t	p	LLCI	ULCI	c_cs
0,45	0,06	7,37	0,00	0,33	0,57	0,33
Direct effect of X on Y						
Effect	se	t	p	LLCI	ULCI	c'_cs
0,21	0,05	4,31	0,00	0,11	0,31	0,16
Indirect effect(s) of X on Y:						
	Effect	BootSE	BootLLCI	BootULCI		

HedPExp	0,24	0,04	0,16	0,32
Completely standardized indirect effect(s) of X on Y:				
	Effect	BootSE	BootLLCI	BootULCI
HedPExp	0,18	0,03	0,12	0,24

Source: Author's calculations
LLCI = Lower Limit Confidence Interval, ULCI = Upper Limit Confidence Interval, SE = Standardised Error, Boot = Bootstrap based on 5000 samples, HedPExp = HPE, cs = coefficient and standard error

4.8.3 HYPOTHESIS 2b

For this mediation hypothesis, ATT is the dependent variable (Y), EE is the independent variable (X) and the mediator variable (M) is UPE.

Mediation is said to have occurred if the strength of the relationship between ATT toward using chatbots and EE associated with chatbots is reduced by including UPE.

Table 4-83 shows that when UPE is not mediating this hypothesis, EE significantly and positively affects the ATT toward using chatbots, β = .45, 95% CI [0.33, 0.57], t = 7.37, p = .00.

The size of the indirect effect and the CI in Table 4-83 is an assessment of the mediation. Table 4-xx shows that there is a significant indirect effect of EE on ATT towards using chatbots through the UPE from using chatbots, β = .31, 95% CI [0.20, 0.43]. The mediation effect is positive.

Therefore, the mediation results support the hypothesis that UPE from using chatbots in the South African financial services industry positively mediates the effect of EE on ATT toward using chatbots.

Table 4-83: Total, direct, and indirect effects (Hypothesis 2b)

TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y						
Total effect of X on Y						
Effect	se	t	p	LLCI	ULCI	c_cs

	0,45	0,06	7,37	0,00	0,33	0,57	0,33
Direct effect of X on Y							
	Effect	se	t	p	LLCI	ULCI	c'_cs
	0,14	0,05	2,88	0,00	0,04	0,23	0,10
Indirect effect(s) of X on Y:							
	Effect	BootSE	BootLLCI	BootULCI			
UtlPExp	0,31	0,06	0,20	0,43			
Completely standardized indirect effect(s) of X on Y:							
	Effect	BootSE	BootLLCI	BootULCI			
UtlPExp	0,23	0,04	0,15	0,32			

Source: Author's calculations

LLCI = Lower Limit Confidence Interval, ULCI = Upper Limit Confidence Interval, SE = Standardised Error, Boot = Bootstrap based on 5000 samples, UtlPExp = UPE, cs = coefficient and standard error

4.8.4 HYPOTHESIS 2c

For this hypothesis, BI (Y) is the dependent variable, the independent variable is HPE (X) and ATT (M) is the mediator variable.

Mediation is said to have occurred if the strength of the relationship between BI to use chatbots and the HPE associated with chatbots is reduced by including ATT towards using chatbots.

Table 4-84 shows that when ATT is not mediating this hypothesis, HPE significantly predicts the BI to use chatbots, $\beta = .77$, 95% CI [0.71, 0.83], $t = 26.19$, $p = .00$.

The size of the indirect effect and the CI in Table 4-84 is an assessment of the mediation by ATT. Table 4-xx shows that there is a significant indirect effect of HPE on the BI to use chatbots through the ATT associated with chatbots, $\beta = .23$, 95% CI [0.18, 0.30]. The mediation effect is positive.

Therefore, the mediation results support the hypothesis that ATT toward using chatbots in the South African financial services industry positively mediates the relationship between HPE and BI to use chatbots.

Table 4-84: Total, direct, and indirect effects (Hypothesis 2c)

TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y							
Total effect of X on Y							
	Effect	se	t	p	LLCI	ULCI	c_cs
	0,77	0,03	26,19	0,00	0,71	0,83	0,78
Direct effect of X on Y							
	Effect	se	t	p	LLCI	ULCI	c'_cs
	0,54	0,04	14,80	0,00	0,47	0,61	0,54
Indirect effect(s) of X on Y:							
	Effect	BootSE	BootLLCI	BootULCI			
Attde	0,23	0,03	0,18	0,30			
Completely standardized indirect effect(s) of X on Y:							
	Effect	BootSE	BootLLCI	BootULCI			
Attde	0,24	0,03	0,18	0,30			

Source: Author's calculations
LLCI = Lower Limit Confidence Interval, ULCI = Upper Limit Confidence Interval, SE = Standardised Error, Boot = Bootstrap based on 5000 samples, Attde = ATT, cs = coefficient and standard error

4.8.5 HYPOTHESIS 2d

BI is the dependent variable (Y), the independent variable is UPE (X) and ATT is the mediator variable (M) for this hypothesis.

Mediation is said to have occurred if the strength of the relationship between BI to use chatbots and the UPE associated with chatbots is reduced by including ATT towards using chatbots.

Table 4-85 shows that when ATT is not mediating this hypothesis, UPE significantly predicts the BI to use chatbots, β = .81, 95% CI [0.74, 0.88], t = 22.15, p = .00.

The size of the indirect effect and the CI in Table 4-85 is an assessment of the mediation by ATT. Table 4-xx shows that there is a significant indirect effect of UPE on the BI to use chatbots through the ATT from using chatbots, β = .32, 95% CI [0.24, 0.41]. The mediation effect is positive.

Therefore, the mediation results support the hypothesis that ATT toward using chatbots in the South African financial services industry positively mediates the relationship between UPE and BI to use chatbots.

Table 4-85: Total, direct, and indirect effects (Hypothesis 2d)

TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y							
Total effect of X on Y							
	Effect	se	t	p	LLCI	ULCI	c_cs
	0,81	0,04	22,15	0,00	0,74	0,88	0,73
Direct effect of X on Y							
	Effect	se	t	p	LLCI	ULCI	c'_cs
	0,49	0,05	10,28	0,00	0,39	0,58	0,44
Indirect effect(s) of X on Y:							
	Effect	BootSE	BootLLCI	BootULCI			
Attde	0,32	0,04	0,24	0,41			
Completely standardized indirect effect(s) of X on Y:							
	Effect	BootSE	BootLLCI	BootULCI			
Attde	0,29	0,04	0,22	0,36			

Source: Author's calculations

LLCI = Lower Limit Confidence Interval, ULCI = Upper Limit Confidence Interval, SE = Standardised Error, Boot = Bootstrap based on 5000 samples, Attde = ATT, cs = coefficient and standard error

4.8.6 HYPOTHESIS 3a

For this hypothesis, PS is the dependent variable and PR is the independent variable.

Table 4-86 shows that there was a negative relationship between PS and PR at *r* = -.51, p < 0.01. The Pearson correlation of -.51 suggests a moderate, negative relationship between PS and PR, and therefore suggesting that as the PR associated with chatbots increases, the PS associated with chatbots in the South African financial services industry decreases.

Table 4-86: Correlations between PR and PS

Correlations			
		Per_Sec	Per_Rsk
Pearson Correlation	Per_Sec	1.000	-0.510
	Per_Rsk	-0.510	1.000
Sig. (1-tailed)	Per_Sec	.	<0,001
	Per_Rsk	0.000	.
N	Per_Sec	440	440
	Per_Rsk	440	440

Source: Author's calculations

Per_Sec = PS, Per_Rsk = PR

The model summary presented in Table 4-87 shows that R-Square = .26, which illustrates that the PR associated with chatbots accounts for 26% of the variation in the PS associated with chatbots in the South African financial services industry.

The Durbin-Watson = 2.027 result indicates that the significance tests for this regression are valid (Field, 2018), additionally, the Durbin-Watson value above 2 indicates a negative correlation between the adjacent residuals.

Table 4-87: Model summary for hypothesis 3a

Model Summary[b]					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	0.510[a]	0.260	0.259	0.60003	2.027
a. Predictors: (Constant), Per_Rsk					
b. Dependent Variable: Per_Sec					

Source: Author's calculations

Per_Sec = PS, Per_Rsk = PR

The ANOVA results in Table 4-88 illustrate that there was a significant effect of PR on PS at $F(1, 438) = 154.24$, $p < 0.01$.

Table 4-88: ANOVA for hypothesis 3a

ANOVA[a]					
Model	Sum of Squares	df	Mean Square	F	Sig.

1	Regression	55.531	1	55.531	154.238	<0,001[b]
	Residual	157.696	438	0.360		
	Total	213.227	439			
a. Dependent Variable: Per_Sec						
b. Predictors: (Constant), Per_Rsk						

Source: Author's calculations

Per_Sec = PS, Per_Rsk = PR

The coefficients Table 4-89 presents the unstandadised β = -.482, p < 0.01 indicating that PR is a significant predictor of the PS associated with chatbots in the South African financial services industry, albeit negative. In other words, an increase in the risk associated with chatbots, results in a decrease in the security of chatbot technology.

Therefore, the correlation and regression results support the hypothesis that the PR of using chatbots in the South African financial services industry has a direct negative impact on PS.

Table 4-89: Coefficients for hypothesis 3a

Coefficients						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.606	0.106		34.069	<0,001
	Per_Rsk	-0.482	0.039	-0.510	-12.419	<0,001

Source: Author's calculations

Per_Rsk = PR

4.8.7 HYPOTHESIS 3b

PT is the dependent variable and PR is the independent variable in this hypothesis.

The correlation was assessed as r = -.329, p < 0.01 in Table 4-90 presenting a significant negative relationship between PR and PT. With r being -.329, this indicates that the relationship between PT and PR is moderate, and negative.

Table 4-90: Correlations between PR and PT

Correlations			
		Per_Trst	Per_Rsk
Pearson Correlation	Per_Trst	1.000	-0.329
	Per_Rsk	-0.329	1.000
Sig. (1-tailed)	Per_Trst	.	<0,001
	Per_Rsk	0.000	.
N	Per_Trst	440	440
	Per_Rsk	440	440

Source: Author's calculations

Per_Rsk = PR, Per_Trst = PT

The model summary presented in Table 4-91 shows that R-Square = .1, which means that PR associated with chatbots can account for 10% of the variation in the PT associated with chatbots in the South African financial services industry.

The Durbin-Watson = 1.948 result indicates that the significance tests for this regression are valid (Field, 2018), additionally, the Durbin-Watson value below 2 indicates a positive correlation between the adjacent residuals.

Table 4-91: Model summary for hypothesis 3b

Model Summary[b]					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	0.329[a]	0.108	0.106	0.59965	1.948
a. Predictors: (Constant), Per_Rsk					
b. Dependent Variable: Per_Trst					

Source: Author's calculations

Note: Per_Rsk = PR, Per_Trst = PT

The ANOVA results for this hypothesis are in Table 4-92, with an F-statistic of 53. The p-value associated with the F-statistic is less than .001 which is significant because it is less than the criterion value of .01. This demonstrates a significant effect of PR on the PT associated with chatbots in the South African financial services industry.

Table 4-92: ANOVA for hypothesis 3b

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	19.058	1	19.058	53.001	<0,001[b]
	Residual	157.496	438	0.360		
	Total	176.554	439			
a. Dependent Variable: Per_Trst						
b. Predictors: (Constant), Per_Rsk						

Source: Author's calculations

Note: Per_Rsk = PR, Per_Trst = PT

The coefficients Table 4-93 presents unstandardised β = -.282, $p < 0.01$ indicating that the PR associated with chatbots is a significant negative predictor of the PT associated with chatbots.

The correlation and regression results support the hypothesis that the PR of using chatbots in the South African financial services industry has a direct negative impact on PT.

Table 4-93: Coefficients for hypothesis 3b

Coefficients						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.406	0.106		32.201	<0,001
	Per_Rsk	-0.282	0.039	-0.329	-7.280	<0,001

Source: Author's calculations

Per_Rsk = PR

4.8.8 HYPOTHESIS 3c

For this hypothesis, HPE is the dependent variable (Y), the independent variable is PR (X) and the mediator variable is UPE (M).

Mediation is said to have occurred if the strength of the relationship between HPE and the PR associated with chatbots is reduced by including UPE.

Table 4-xx shows that when UPE is not mediating this hypothesis, PR has a statistically significant negative relationship with the HPE associated with chatbots, β = -.23, 95% CI [-0.32, -0.13], t = -4.74, p = .00.

The size of the indirect effect and the CI in Table 4-94 is an assessment of the mediation by UPE. Table 4-94 shows that there is a significant negative indirect effect of PR on HPE associated with chatbots through the UPE from using chatbots, β = -.11, 95% CI [-0.18, -0.03].

Therefore, the mediation results support the hypothesis that the UPE of using chatbots in the South African financial services industry negatively mediates the relationship between PR and HPE.

Table 4-94: Total, direct, and indirect effects (Hypothesis 3c)

TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y							
Total effect of X on Y							
	Effect	se	t	p	LLCI	ULCI	c_cs
	-0,23	0,05	-4,74	0,00	-0,32	-0,13	-0,22
Direct effect of X on Y							
	Effect	se	t	p	LLCI	ULCI	c'_cs
	-0,12	0,04	-3,20	0,00	-0,19	-0,05	-0,12
Indirect effect(s) of X on Y:							
	Effect	BootSE	BootLLCI	BootULCI			
UtlPExp	-0,11	0,04	-0,18	-0,03			
Completely standardized indirect effect(s) of X on Y:							
	Effect	BootSE	BootLLCI	BootULCI			
UtlPExp	-0,10	0,04	-0,18	-0,03			

Source: Author's calculations
LLCI = Lower Limit Confidence Interval, ULCI = Upper Limit Confidence Interval, SE = Standardised Error, Boot = Bootstrap based on 5000 samples, UtlPExp = UPE, cs = coefficient and standard error

4.8.9 HYPOTHESIS 4

For H4, HPE is the dependent variable and UPE is the independent variable.

The correlation is r = 0.655, p < 0.01 displaying a significantly strong positive relationship between HPE and UPE in Table 4-95.

Table 4-95: Correlations between HPE and UPE

Correlations			
		HedPExp	UtlPExp
Pearson Correlation	HedPExp	1.000	0.655
	UtlPExp	0.655	1.000
Sig. (1-tailed)	HedPExp	.	<0,001
	UtlPExp	0.000	.
N	HedPExp	440	440
	UtlPExp	440	440

Source: Author's calculations

Note: UtlPExp = UPE, HedPExp = HPE

The model summary presented in Table 4-96 shows that R-Square = .429, which means that UPE associated with chatbots can account for 43% of the variation in the HPE associated with chatbots in the South African financial services industry.

The Durbin-Watson = 1.899 result indicates that the significance tests for this regression are valid (Field, 2018), additionally, the Durbin-Watson value below 2 indicates a positive correlation between the adjacent residuals.

Table 4-96: Model summary for hypothesis 4

Model Summary[b]					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	0.655[a]	0.429	0.428	0.57629	1.899

a. Predictors: (Constant), UtlPExp
b. Dependent Variable: HedPExp

Source: Author's calculations

Note: UtlPExp = UPE, HedPExp = HPE

Table 4-97 presents the ANOVA results for this regression. The ANOVA results illustrate that there was a significant effect of UPE on HPE associated with chatbots at $F(1, 438) = 329.29$, $p < 0.001$.

Table 4-97: ANOVA for hypothesis 4

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	109.363	1	109.363	329.293	<0,001[b]
	Residual	145.466	438	0.332		
	Total	254.828	439			
a. Dependent Variable: HedPExp						
b. Predictors: (Constant), UtlPExp						

Source: Author's calculations

UtlPExp = UPE, HedPExp = HPE

The coefficients Table 4-98 presents unstandardised $\beta = .737$, $p < 0.01$ indicating that the UPE associated with chatbots is a significant predictor of the HPE associated with chatbots in the South African financial services industry.

The correlation and regression results support the hypothesis that the UPE in using chatbots in the South African financial services industry has a direct positive impact on the HPE of chatbots.

Table 4-98: Coefficients for hypothesis 4

Coefficients						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	0.508	0.117		4.329	<0,001
	UtlPExp	0.737	0.041	0.655	18.146	<0,001

Source: Author's calculations

Note: UtlPExp = UPE

4.8.10 HYPOTHESIS 5a

BI is the dependent variable (Y), the independent variable is PS (X) and ATT is the mediator variable (M) for this hypothesis.

Mediation is said to have occurred if the strength of the relationship between BI to use chatbots and the PS associated with chatbots is reduced by including ATT towards using chatbots.

Table 4-xx shows that when ATT is not mediating this hypothesis, PS significantly predicts the BI to use chatbots, β = .54, 95% CI [0.45, 0.62], t = 11.95, p = .00.

The size of the indirect effect and the CI in Table 4-99 is an assessment of the mediation by ATT. Table 4-99 shows that there is a significant indirect effect of PS on the BI to use chatbots through the ATT from using chatbots, β = .31, 95% CI [0.25, 0.38]. The mediation effect is positive.

Therefore, the mediation results support the hypothesis that ATT toward using chatbots in the South African financial services industry positively mediates the relationship between UPE and BI to use chatbots.

Table 4-99: Total, direct, and indirect effects (Hypothesis 5a)

TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y							
Total effect of X on Y							
	Effect	se	t	p	LLCI	ULCI	c_cs
	0,54	0,04	11,95	0,00	0,45	0,62	0,50
Direct effect of X on Y							
	Effect	se	t	p	LLCI	ULCI	c'_cs
	0,22	0,04	5,66	0,00	0,15	0,30	0,21
Indirect effect(s) of X on Y:							
	Effect	BootSE	BootLLCI	BootULCI			
Attde	0,31	0,03	0,25	0,38			
Completely standardized indirect effect(s) of X on Y:							

	Effect	BootSE	BootLLCI	BootULCI
Attde	0,29	0,03	0,23	0,35

Source: Author's calculations

LLCI = Lower Limit Confidence Interval, ULCI = Upper Limit Confidence Interval, SE = Standardised Error, Boot = Bootstrap based on 5000 samples, Attde = ATT, cs = coefficient and standard error

4.8.11 HYPOTHESIS 5b

For this hypothesis, the relationship between PS (dependent variable) and SI (independent variable) was assessed.

Table 4-100 presents the correlation $r = .41$, $p < 0.01$ indicating a statistically significant positive relationship. The correlation of .41 indicates a moderate relationship between PS and SI.

Table 4-100: Correlation between PS and SI

Correlations			
		Per_Sec	Sc_Infl
Pearson Correlation	Per_Sec	1.000	0.410
	Sc_Infl	0.410	1.000
Sig. (1-tailed)	Per_Sec	.	<0,001
	Sc_Infl	0.000	.
N	Per_Sec	440	440
	Sc_Infl	440	440

Source: Author's calculations

Note: Per_Sec = PS, Sc_Infl = SI

The model summary presented in Table 4-101 shows that R-Square = .168, which means that SI can account for almost 17% of the variation in the PS associated with chatbots in the South African financial services industry.

The Durbin-Watson = 1.834 result indicates that the significance tests for this regression are valid (Field, 2018).

Table 4-101: Model summary for hypothesis 5b

Model Summary[b]					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	0.410[a]	0.168	0.167	0.63626	1.834
a. Predictors: (Constant), Sc_Infl					
b. Dependent Variable: Per_Sec					

Source: Author's calculations

The ANOVA results in Table 4-102 illustrate that there was a significant effect of SI on PS associated with chatbots at $F(1, 438) = 88.72$, $p < 0.001$ for this regression.

Table 4-102: ANOVA for hypothesis 5b

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	35.915	1	35.915	88.717	<0,001[b]
	Residual	177.312	438	0.405		
	Total	213.227	439			
a. Dependent Variable: Per_Sec						
b. Predictors: (Constant), Sc_Infl						

Source: Author's calculations

The coefficients Table 4-103 presents unstandardised $\beta = .407$, $p < 0.01$ indicating that SI of accepting chatbots has a significant influence on the PS associated with chatbots in the South African financial services industry.

The correlation and regression results support the hypothesis that the SI of accepting chatbots in the South African financial services industry positively and directly influences PS.

Table 4-103: Coefficients for hypothesis 5b

Coefficients						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.426	0.102		14.008	<0,001
	Sc_Infl	0.407	0.043	0.410	9.419	<0,001

Source: Author's calculations

4.8.12 HYPOTHESIS 6

For this hypothesis, EE is the dependent variable and SE is the independent variable.

The Pearson correlation of these two variables is presented in Table 4-104 and it is insignificant as *r* = -.066, p = .083. The strength of the relationship between EE and SE is weak, and negative. The p-value associated with this correlation is statistically insignificant as it is more than .01.

Table 4-104: Correlations for EE and SE

Correlations			
		Eff_Exp	Slf_Effy
Pearson Correlation	Eff_Exp	1.000	-0.066
	Slf_Effy	-0.066	1.000
Sig. (1-tailed)	Eff_Exp	.	0.083
	Slf_Effy	0.083	.
N	Eff_Exp	440	440
	Slf_Effy	440	440

Source: Author's calculations

The model summary presented in Table 4-105 shows that R-Square = .004, which means an individual's SE perceptions associated with chatbots can only account for 0.4% of the variation in the EE in learning and using chatbots in the South African financial services industry

Table 4-105: Model summary for hypothesis 6

Model Summary[b]					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	0.066[a]	0.004	0.002	0.56663	2.051
a. Predictors: (Constant), Slf_Effy					
b. Dependent Variable: Eff_Exp					

Source: Author's calculations

The ANOVA results in Table 4-106 illustrate that there is an insignificant effect of an individual's SE perceptions on the EE in learning and using chatbots at F(1, 438) =

1.92, p = .166 for this regression. The p-value of greater than .01 demonstrates the insignificant effect.

Table 4-106: ANOVA for hypothesis 6

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	0.617	1	0.617	1.921	0.166[b]
	Residual	140.631	438	0.321		
	Total	141.247	439			
a. Dependent Variable: Eff_Exp						
b. Predictors: (Constant), Slf_Effy						

Source: Author's calculations

Additionally, the coefficients in Table 4-107 present an unstandardised β = -.06, p = 0.166, indicating that SE has an insignificant effect on the EE in learning and using chatbots.

The correlation and regression results therefore reject the hypothesis that an individual's SE perceptions negatively and directly affect the amount of EE in learning and using chatbots in the South African financial services industry.

Table 4-107: Coefficients for hypothesis 6

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.275	0.129		25.436	<0,001
	Slf_Effy	-0.064	0.046	-0.066	-1.386	0.166

Source: Author's calculations

4.8.13 HYPOTHESIS 7a

PT is the dependent variable and PS is the independent variable in this hypothesis.

Table 4-108 presents the correlation as *r* = .532, p < 0.001, indicating a statistically significantly moderate positive relationship.

Table 4-108: Correlations between PS and PT

Correlations			
		Per_Trst	Per_Sec
Pearson Correlation	Per_Trst	1.000	0.532
	Per_Sec	0.532	1.000
Sig. (1-tailed)	Per_Trst	.	<0,001
	Per_Sec	0.000	.
N	Per_Trst	440	440
	Per_Sec	440	440

Source: Author's calculations

The model summary presented in Table 4-109 shows that R-Square = .284, which means that the PS associated with chatbots can account for 28% of the variation in the PT associated with chatbots in the South African financial services industry.

Table 4-109: Model summary for hypothesis 7a

Model Summary[b]					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	0.532[a]	0.284	0.282	0.53741	1.939
a. Predictors: (Constant), Per_Sec					
b. Dependent Variable: Per_Trst					

Source: Author's calculations

The ANOVA results in Table 4-110 illustrate that there is a significant effect of the PS associated with chatbots on the PT at $F(1, 438) = 173.319$, $p < 0.001$ for this regression.

Table 4-110: ANOVA for hypothesis 7a

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	50.056	1	50.056	173.319	<0,001[b]
	Residual	126.498	438	0.289		
	Total	176.554	439			
a. Dependent Variable: Per_Trst						
b. Predictors: (Constant), Per_Sec						

Source: Author's calculations

Additionally, the coefficients in Table 4-111 present an unstandardised β = .485, p < 0.001, indicating that PS has a significant effect on the PT associated with chatbots.

Table 4-111: Coefficients for hypothesis 7a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.531	0.090		17.033	<0,001
	Per_Sec	0.485	0.037	0.532	13.165	<0,001

Source: Author's calculations

The correlation and regression results therefore support the hypothesis that PS of chatbots in the South African financial services industry positively and directly predicts PT.

4.8.14 HYPOTHESIS 7b

In this hypothesis, EE is the dependent variable and PT is the independent variable.

Table 4-112 shows that the Pearson correlation between these two variables is r = .237, with p < 0.001, presenting a significant positive relationship.

Table 4-112: Correlations for EE and PT

Correlations			
		Eff_Exp	Per_Trst
Pearson Correlation	Eff_Exp	1.000	0.237
	Per_Trst	0.237	1.000
Sig. (1-tailed)	Eff_Exp	.	<0,001
	Per_Trst	0.000	.
N	Eff_Exp	440	440
	Per_Trst	440	440

Source: Author's calculations

The model summary presented in Table 4-113 shows that R-Square = .056, which means that the PT associated with chatbots can account for 5,6% of the variation in the EE tolerance that individuals need to continue learning and using chatbots in the South African financial services industry.

Table 4-113: Model summary for hypothesis 7b

Model Summary[b]					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	0.237[a]	0.056	0.054	0.55167	2.011
a. Predictors: (Constant), Per_Trst					
b. Dependent Variable: Eff_Exp					

Source: Author's calculations

The ANOVA results in Table 4-114 illustrate that there is a statistically significant effect of the PT associated with chatbots on the EE tolerance of individuals at $F(1, 438) = 26.1$, $p < 0.001$ for this regression.

Table 4-114: ANOVA for hypothesis 7b

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	7.944	1	7.944	26.104	<0,001[b]
	Residual	133.303	438	0.304		
	Total	141.247	439			
a. Dependent Variable: Eff_Exp						
b. Predictors: (Constant), Per_Trst						

Source: Author's calculations

Additionally, the coefficients in Table 4-115 present an unstandardised $\beta = .212$, $p < 0.001$, indicating that PT has a significant effect on the EE associated with chatbots.

The correlation and regression results therefore support the hypothesis that PT in chatbots in the South African financial services industry directly increases the amount of EE tolerance individuals need to continue learning and using chatbots.

Table 4-115: Coefficients for hypothesis 7b

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	2.535	0.114		22.292	<0,001
	Per_Trst	0.212	0.042	0.237	5.109	<0,001

Source: Author's calculations

4.8.15 HYPOTHESIS 7c

BI is the dependent variable, and PT is the independent variable in this hypothesis.

Table 4-116 shows that the correlation is r = .536, $p < 0.001$ illustrating a significant positive relationship between the PT in chatbots in the South African financial services industry and the BI to use chatbots.

Table 4-116: Correlations for BI and PT

Correlations			
		Beh_Int	Per_Trst
Pearson Correlation	Beh_Int	1.000	0.536
	Per_Trst	0.536	1.000
Sig. (1-tailed)	Beh_Int	.	<0,001
	Per_Trst	0.000	.
N	Beh_Int	440	440
	Per_Trst	440	440

Source: Author's calculations

The model summary presented in Table 4-117 shows that R-Square = .288, which means that the PT in chatbots can account for almost 29% of the variation in the BI to use chatbots.

Table 4-117: Model summary for hypothesis 7c

Model Summary[b]					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	0.536[a]	0.288	0.286	0.63698	1.950
a. Predictors: (Constant), Per_Trst					
b. Dependent Variable: Beh_Int					

Source: Author's calculations

The ANOVA results in Table 4-118 illustrate that there is a statistically significant effect of the PT associated with chatbots on the BI of individuals to use chatbots at $F(1, 438) = 176.786$, $p < 0.001$.

Table 4-118: ANOVA for hypothesis 7c

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	71.730	1	71.730	176.786	<0,001[b]
	Residual	177.715	438	0.406		
	Total	249.444	439			
a. Dependent Variable: Beh_Int						
b. Predictors: (Constant), Per_Trst						

Source: Author's calculations

The coefficients in Table 4-119 present an unstandardised $\beta = .637$, $p < 0.001$, indicating that PT has a significant effect on the BI of individuals to use chatbots.

The correlation and regression results therefore support the hypothesis that PT in chatbots in the South African financial services industry positively and directly predicts the BI to use chatbots.

Table 4-119: Coefficients for hypothesis 7c

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	0.960	0.131		7.313	<0,001

	Per_Trst	0.637	0.048	0.536	13.296	<0,001

Source: Author's calculations

4.8.16 HYPOTHESIS 7d

For H7d, PT is the independent variable and HPE is the dependent variable.

Table 4-120 presents the correlations. The Pearson correlation is significant, and positive at r = .489, $p < 0.001$. The strength of the relationship between PT and HPE is moderate.

Table 4-120: Correlations for HPE and PT

Correlations			
		HedPExp	Per_Trst
Pearson Correlation	HedPExp	1.000	0.489
	Per_Trst	0.489	1.000
Sig. (1-tailed)	HedPExp	.	<0,001
	Per_Trst	0.000	.
N	HedPExp	440	440
	Per_Trst	440	440

Source: Author's calculations

The model summary presented in Table 4-121 shows that R-Square = .239, which means that the PT in chatbots can account for almost 24% of the variation in the HPE associated with chatbots.

Table 4-121: Model summary for hypothesis 7d

Model Summary[b]					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	0.489[a]	0.239	0.237	0.66537	1.898
a. Predictors: (Constant), Per_Trst					
b. Dependent Variable: HedPExp					

Source: Author's calculations

The ANOVA results in Table 4-122 illustrate that there is a statistically significant effect of the PT associated with chatbots on the HPE associated with chatbots at $F(1, 438) = 137.59$, $p < 0.001$.

Table 4-122: ANOVA for hypothesis 7d

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	60.915	1	60.915	137.592	<0,001[b]
	Residual	193.913	438	0.443		
	Total	254.828	439			
a. Dependent Variable: HedPExp						
b. Predictors: (Constant), Per_Trst						

Source: Author's calculations

Additionally, the coefficients in Table 4-123 present an unstandardised β = .587, $p < 0.001$, indicating that the PT associated with chatbots has a significant effect on the HPE.

The correlation and regression results therefore support the hypothesis that PT for chatbots in the South African financial services industry positively impacts HPE.

Table 4-123: Coefficients for hypothesis 7d

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.015	0.137		7.398	<0,001
	Per_Trst	0.587	0.050	0.489	11.730	<0,001

Source: Author's calculations

4.8.17 HYPOTHESIS 7e

UPE is the dependent variable and PT is the independent variable in this hypothesis. The correlation is presented in Table 4-124. The correlation between PT and UPE is significantly positive at r = .530, p < 0.001. The strength of the correlation is moderate.

Table 4-124: Correlations for UPE and PT

Correlations			
		UtlPExp	Per_Trst
Pearson Correlation	UtlPExp	1.000	0.530
	Per_Trst	0.530	1.000
Sig. (1-tailed)	UtlPExp	.	<0,001
	Per_Trst	0.000	.
N	UtlPExp	440	440
	Per_Trst	440	440

Source: Author's calculations

The model summary presented in Table 4-125 shows that R-Square = .281, which means that the PT in chatbots can account for 28% of the variation in the UPE associated with chatbots.

Table 4-125: Model summary for hypothesis 7e

Model Summary[b]					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	0.530[a]	0.281	0.280	0.57507	2.083
a. Predictors: (Constant), Per_Trst					
b. Dependent Variable: UtlPExp					

Source: Author's calculations

The ANOVA results in Table 4-126 illustrate that there is a statistically significant effect of the PT associated with chatbots on the UPE associated with chatbots at F(1, 438) = 171.3, p < 0.001.

Table 4-126: ANOVA for hypothesis 7e

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	56.651	1	56.651	171.304	<0,001[b]
	Residual	144.849	438	0.331		
	Total	201.500	439			
a. Dependent Variable: UtlPExp						
b. Predictors: (Constant), Per_Trst						

Source: Author's calculations

Furthermore, the coefficients in Table 4-127 present an unstandardised β = .566, p < 0.001, indicating that the PT associated with chatbots has a significant effect on the UPE.

The correlation and regression results therefore support the hypothesis that PT for chatbots in the South African financial services industry positively impacts UPE.

Table 4-127: Coefficients for hypothesis 7e

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.302	0.119		10.987	<0,001
	Per_Trst	0.566	0.043	0.530	13.088	<0,001

Source: Author's calculations

4.8.18 HYPOTHESIS 8a

For this hypothesis, BI is the dependent variable and SI is the independent variable.

Table 4-128 presents the Pearson correlation is significant and positive at r = .525, p < 0.001. indicating a moderate positive relationship between BI and SI.

Table 4-128: Correlations for BI and SI

Correlations			
		Beh_Int	Sc_Infl
Pearson Correlation	Beh_Int	1.000	0.525
	Sc_Infl	0.525	1.000

Sig. (1-tailed)	Beh_Int	.	<0,001
	Sc_Infl	0.000	.
N	Beh_Int	440	440
	Sc_Infl	440	440

Source: Author's calculations

The model summary presented in Table 4-129 shows that R-Square = .276, which means that the SI in accepting chatbots can account for almost 28% of the variation in the BI to use chatbots.

Table 4-129: Model summary for hypothesis 8a

Model Summary[b]					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	0.525[a]	0.276	0.274	0.64208	1.894
a. Predictors: (Constant), Sc_Infl					
b. Dependent Variable: Beh_Int					

Source: Author's calculations

The ANOVA results in Table 4-130 illustrate that there is a statistically significant effect of the SI in accepting chatbots on the BI to use chatbots at $F(1, 438) = 167.1$, $p < 0.001$.

Table 4-130: ANOVA for hypothesis 8a

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	68.873	1	68.873	167.060	<0,001[b]
	Residual	180.572	438	0.412		
	Total	249.444	439			
a. Dependent Variable: Beh_Int						
b. Predictors: (Constant), Sc_Infl						

Source: Author's calculations

Furthermore, the coefficients in Table 4-131 present an unstandardised β = .563, $p < 0.001$, indicating that the SI in chatbots has a significant effect on the BI to accept chatbots.

The correlation and regression results therefore support the hypothesis that the SI of accepting chatbots in the South African financial services industry positively affects the BI to use chatbots.

Table 4-131: Coefficients for hypothesis 8a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.392	0.103		13.550	<0,001
	Sc_Infl	0.563	0.044	0.525	12.925	<0,001

Source: Author’s calculations

4.8.19 HYPOTHESIS 8b

For hypothesis 8b, HPE is the dependent variable and SI is the independent variable.

The Pearson correlation is significant and positive at *r* = 0.478, p < 0.001, presented in Table 4-132 The correlation also shows that the strength of the relationship between SI and HPE is moderate.

Table 4-132: Correlations for HPE and SI

Correlations			
		HedPExp	Sc_Infl
Pearson Correlation	HedPExp	1.000	0.478
	Sc_Infl	0.478	1.000
Sig. (1-tailed)	HedPExp	.	<0,001
	Sc_Infl	0.000	.
N	HedPExp	440	440
	Sc_Infl	440	440

Source: Author’s calculations

The model summary presented in Table 4-133 shows that R-Square = .228, which means that the SI in accepting chatbots can account for almost 23% of the variation in the HPE in chatbots.

Table 4-133: Model summary for hypothesis 8b

Model Summary[b]					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	0.478[a]	0.228	0.226	0.67009	1.907
a. Predictors: (Constant), Sc_Infl					
b. Dependent Variable: HedPExp					

Source: Author's calculations

The ANOVA results in Table 4-134 illustrate that there is a statistically significant effect of the SI in accepting chatbots in the South African financial services industry on the HPE related to chatbots at $F(1, 438) = 129.514$, $p < 0.001$.

Table 4-134: ANOVA for hypothesis 8b

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	58.155	1	58.155	129.514	<0,001[b]
	Residual	196.673	438	0.449		
	Total	254.828	439			
a. Dependent Variable: HedPExp						
b. Predictors: (Constant), Sc_Infl						

Source: Author's calculations

And finally, the coefficients in Table 4-135 present an unstandardised β = .518, $p < 0.001$, indicating that the SI of accepting chatbots has a significant effect on the HPE related to chatbots.

The correlation and regression results therefore support the hypothesis that the SI of accepting chatbots in the South African financial services industry directly and positively impacts HPE related to chatbots.

Table 4-135: Coefficients for hypothesis 8b

Model	Unstandardized Coefficients	Standardized Coefficients	t	Sig.

		B	Std. Error	Beta		
1	(Constant)	1.416	0.107		13.208	<0,001
	Sc_Infl	0.518	0.045	0.478	11.380	<0,001

Source: Author’s calculations

4.8.20 HYPOTHESIS 8c

UPE is the dependent variable and SI is the independent variable in this hypothesis. The Pearson correlation is statistically significant and positive at r = .435, $p < 0.001$ as presented in Table 4-136. The correlation also shows that the strength of the relationship between SI and UPE is moderate.

Table 4-136: Correlations for UPE and SI

Correlations			
		UtlPExp	Sc_Infl
Pearson Correlation	UtlPExp	1.000	0.435
	Sc_Infl	0.435	1.000
Sig. (1-tailed)	UtlPExp	.	<0,001
	Sc_Infl	0.000	.
N	UtlPExp	440	440
	Sc_Infl	440	440

Source: Author’s calculations

The model summary presented in Table 4-137 shows that R-Square = .189, which means that the SI in accepting chatbots can account for almost 19% of the variation in the UPE related to chatbots.

Table 4-137: Model summary for hypothesis 8c

Model Summary[b]					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	0.435[a]	0.189	0.187	0.61086	2.047
a. Predictors: (Constant), Sc_Infl					
b. Dependent Variable: UtlPExp					

Source: Author’s calculations

The ANOVA results in Table 4-138 illustrate that there is a statistically significant effect of the SI in accepting chatbots in the South African financial services industry on the UPE related to chatbots at $F(1, 438) = 101.99$, $p < 0.001$.

Table 4-138: ANOVA for hypothesis 8c

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	38.059	1	38.059	101.992	<0,001[b]
	Residual	163.441	438	0.373		
	Total	201.500	439			
a. Dependent Variable: UtlPExp						
b. Predictors: (Constant), Sc_Infl						

Source: Author's calculations

Additionally, the coefficients in Table 4-139 present an unstandardised β = .419, p < 0.001, indicating that the SI of accepting chatbots has a significant effect on the UPE related to chatbots.

Table 4-139: Coefficients for hypothesis 8b

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.870	0.098		19.139	<0,001
	Sc_Infl	0.419	0.041	0.435	10.099	<0,001

Source: Author's calculations

The correlation and regression results therefore support the hypothesis that the SI of accepting chatbots in the South African financial services industry directly and positively impacts UPE related to chatbots.

4.8.21 HYPOTHESIS 9

Table 4-140, Table 4-141 and Table 4-142 present the results of the moderation analysis. For this hypothesis, the paths that affect the BI were tested for the moderating effect of gender. All five paths were significant for females, and four out of the five paths were significant for males, with the only insignificant path being FC -> BI for males. All the five paths were statistically insignificant for the respondents who preferred to not state their gender, and finally, the paths could not be tested for the 1 respondent that identified as non-binary because regression was not possible for only one observation.

For both females and males, the path with the highest effect is ATT -> BI at $\beta = 0.68$, $p < .001$ and $\beta = .75$, $p < .001$, respectively. The path with the lowest effect, is FC -> BI at $\beta = .2$, $p = 0.01$ for females, and $\beta = .117$, $p = .205$ for males. This indicates that FC are not an important determinant of BI for males.

Considering the β effects and the p-values across the gender groups, the hypothesis that gender moderates the BI relationships in the research model is partially supported. This is also considering that 11 respondents were excluded from the testing of this hypothesis.

Table 4-140: Moderation effects (Gender)

Path	Gender					
	Female (N = 284)		Male (N = 184)		Prefer not to say (N = 11)	
	β effect	p-value	β effect	p-value	β effect	p-value
FC => BI	0.198	0.010	0.117	0.205	-0.331	0.504
ATT => BI	0.680	<0,001	0.747	<0,001	0.718	0.007
PT => BI	0.620	<0,001	0.644	<0,001	0.638	0.117
SI => BI	0.483	<0,001	0.641	<0,001	0.824	0.011
PS => BI	0.530	<0,001	0.525	<0,001	0.676	0.025

Source: Author's calculations

The paths that affect the BI to adopt chatbots were tested for the moderating effect of age. Four of the five paths were significant for the respondents aged 18 – 55, who made up 95% of the sample (420 respondents), while none of the paths were significant for the respondents who preferred not to indicate their age. The FC -> BI path was insignificant across all age groups, and for the respondents who preferred to not state their age.

Although the moderation effects of age are evident when considering the β effects and the p-values in Table 4-xx, the hypothesis cannot be fully supported due to some effects being insignificant for some age groups. As such, the hypothesis that age moderates the BI relationships in the research model is partially supported.

Table 4-141: Moderation effects (Age)

	Age group													
Path	Under 18 (N = 10)		18-25 (N = 101)		26-35 (N = 193)		36-45 (N = 104)		46-55 (N = 22)		56-65 (N = 6)		Prefer not to say (N = 4)	
	β effect	p-value	β effect	p-value	β effect	p-value	β effect	p-value	β effect	p-value	β effect	p-value	β effect	p-value
FC => BI	0.315	0.668	0.227	0.090	0.117	0.173	0.168	0.125	0.512	0.076	1.491	0.347	1.364	0.130
ATT => BI	0.977	0.009	0.668	<0,001	0.750	<0,001	0.649	<0,001	0.935	<0,001	1.076	0.177	0.268	0.427
PT => BI	1.028	<0,001	0.794	<0,001	0.674	<0,001	0.454	<0,001	0.859	<0,001	0.184	0.745	0.500	0.529
SI => BI	0.855	0.010	0.605	<0,001	0.557	<0,001	0.564	<0,001	1.003	<0,001	-0.950	0.095	0.778	0.222
PS => BI	2.464	<0,001	0.593	<0,001	0.501	<0,001	0.440	<0,001	0.657	0.002	1.150	0.017	0.583	0.222

Source: Author's calculations

The paths that affect the BI to adopt chatbots were tested for the moderating effect of previous chatbot experience and the results are presented in Table 4-xx. Four of the five paths were significant for the respondents who do not have prior experience of using chatbots, with the only insignificant path being FC -> BI.

Among the respondents who do have prior chatbot experience, the PT -> BI and SI -> BI paths are both significant, indicating that the promise of a chatbot performing as expected and the opinions of social circles is important for individuals who have prior experience of using chatbots.

Considering the β effects and the p-values in Table 4-xx, the moderating effects of previous experience are evident, however not consistent between individuals with prior experience and those without.

Table 4-142: Moderation effects (Previous experience)

	Previous experience							
	No		Yes					
Path	Never (N = 154)		Sometimes (N = 228)		Most times (N = 50)		Always (N = 8)	
	β effect	p-value	β effect	p-value	β effect	p-value	β effect	p-value
FC => BI	-0.008	0.936	0.168	0.033	0.513	0.002	-0.090	0.883
ATT => BI	0.752	<0,001	0.633	<0,001	0.712	<0,001	0.588	0.026
PT => BI	0.709	<0,001	0.526	<0,001	0.634	<0,001	0.862	0.002
SI => BI	0.658	<0,001	0.417	<0,001	0.556	<0,001	0.823	0.004
PS => BI	0.650	<0,001	0.395	<0,001	0.504	<0,001	0.778	0.012

Source: Author's calculations

4.9 SUMMARY OF THE RESULTS

Table 4-143 presented the hypotheses test results and indicates the effect sizes, measured by unstandized β as well as the decision to accept or reject the hypotheses.

Table 4-143: Hypotheses test summary results

Hypotheses	Independent variable	Dependent variable	Mediating variable	Moderating variable	Effect size (β)	Decision
H1	FC	BI	-	-	0.172	Supported
H2a	EE	HPE	ATT	-	0.24	Supported
H2b	EE	UPE	ATT	-	0.31	Supported
H2c	HPE	ATT	BI	-	0.23	Supported
H2d	UPE	ATT	BI	-	0.32	Supported
H3a	PR	PS	-		-0.482	Supported
H3b	PR	PT	-		-0.282	Supported
H3c	PR	UPE	HPE	-	-0.11	Supported
H4	UPE	HPE	-	-	0.737	Supported
H5a	PS	BI	ATT	-	0.31	Supported
H5b	SI	PS	-	-	0.407	Supported
H6	SE	EE	-	-	-0.064	Rejected
H7a	PS	PT	-	-	0.485	Supported
H7b	PT	EE	-	-	0.212	Supported
H7c	PT	BI	-	-	0.637	Supported
H7d	PT	HPE	-	-	0.587	Supported
H7e	PT	UPE	-	-	0.566	Supported
H8a	SI	BI	-	-	0.563	Supported
H8b	SI	HPE	-	-	0.518	Supported
H8c	SI	UPE	-	-	0.419	Supported

Source: Author's calculations

4.10 CHAPTER SUMMARY

In summary, the above results presented evidence that only 1 of the hypotheses developed in Chapter 2 is insignificant in the overall research model. This illustrates that in general, the UTAUT constructs, ATT from TAM and security-related constructs are key determining factor that influence the adoption of chatbots in South Africa. The data presented however shows that SE of chatbots is an insignificant factor and does not have any effect on chatbot adoption.

In addition, the evidence presented in this chapter shows that there is reason to believe that gender, age, and previous chatbot experience could be factors that offer insight to chatbot adoption. There also seems to be indication that the significance effects differ based on gender, age, and chatbot adoption.

Assessing the data for assumptions, verifying the internal consistency, and performing exploratory factor analysis for this study solidifies the results presented. And finally, using regression analysis together with correlations to assess the hypotheses provided a thorough evaluation of the hypotheses developed in this study.

5 CHAPTER 5. DISCUSSION OF THE RESULTS

5.1 INTRODUCTION

This chapter discusses the results presented in Chapter 4. The evidence presented in Chapter 4 offers strong support for the conceptual model in Figure 2, and the hypotheses developed in Chapter 2, with only 1 hypothesis being rejected, namely, the negative impact of SE on EE.

5.2 HYPOTHESES DISCUSSIONS

5.2.1 HYPOTHESIS 1

The results of this study found that FC do indeed have a positive effect on the BI to use chatbots. The relationship between FC for using chatbots in the South African financial services industry and the BI of individuals to use chatbots has been confirmed. Although the relationship is statistically significant, the result indicated that the influence of FC on BI is however, quite weak.

This result differs from most prior studies that have found FC associated with technology to have an insignificant impact on the BI to use technology as theorised in the UTAUT (Venkatesh et al., 2003; Baptista & Oliviera, 2015; Khalilzadeh, Ozturk & Bilgihan, 2017). Comparatively, the variation in the results of this study to most prior studies depend on the inclusion or exclusion of the EE construct in the conceptual framework applied. The UTAUT posits that the EE construct largely incorporates issues related to technical support and barriers to use the technology, which is the essence of the FC construct (Venkatesh et al., 2003). As is the case in this study, if EE is present in the conceptual framework, the effect of FC on BI becomes weak or insignificant (Venkatesh et al., 2003).

Of the 440 respondents in this study, 35% (154 respondents) indicated to have never used chatbots, and this may be due to a lack of resources or knowledge of chatbots. Overall, the results of this study indicate that individuals in the South African financial services industry place importance on the resources, support, and knowledge required to adopt chatbots, i.e., the FC, though the effect is not as strong as would be expected.

Noteworthy however, prior studies have found that FC have an impact on actual use behaviour, which was not hypothesized in this study, rather than BI (Khalilzadeh, Ozturk & Bilgihan, 2017; Ling et al., 2019). And, interestingly, and although not hypothesized in this study, FC associated with technology have been confirmed to have a significant effect on EE (Khalilzadeh, Ozturk & Bilgihan, 2017).

5.2.2 HYPOTHESIS 2a

The results of this study found that HPE from using chatbots in the South African financial services industry positively mediates the effect of EE on ATT toward using chatbots.

Khalilzadeh, Ozturk and Bilgihan (2017) also found a positive mediating effect of HPE on EE and ATT, however, Yang (2010) suggested otherwise, and further found that HPE has a more critical effect than UPE.

This difference in judgement could be emanating from the different technology contexts applied in these studies. While Yang (2010) considered mobile shopping contexts which are generally more concerned with entertainment and fun aspects, this study considered chatbots, which are generally concerned with task performance (Simonite, 2017), and Khalilzadeh, Ozturk and Bilgihan (2017) considered near-field communication payment methods which are also more concerned with utilitarian aspects of performance expectancy. Individuals may perceive chatbot use as a means to fulfil a task, rather than an entertaining experience (Lee & Lyu, 2016). This therefore resulted in a lower effect of HPE, and higher effect for UPE.

5.2.3 HYPOTHESIS 2b

In line with the findings by Yang (2010), Khalilzadeh, Ozturk and Bilgihan (2017), and Chan et al. (2022), this study found that UPE from using chatbots positively mediates the effect of EE on ATT toward using chatbots. Chan et al. (2022) asserted that EE can strengthen UPE. This means that, the easier chatbots are to use, the more useful individuals will perceive them.

A stronger path coefficient was produced for the effect of UPE in comparison to HPE. This might be attributed to the fact that chatbots are more concerned with utilitarian aspects as individuals prioritise task performance over entertainment. Chatbots must be well programmed and configured to handle any given task to perform as intended (Simonite, 2017). If technology is made easier to use, it will be perceived to be more useful, and on the other hand, if ease of use is not prioritised, EE and ATT towards technology will be insignificant (Baptista & Oliviera, 2015; Chan et al., 2022).

Furthermore, Zhao and Bacao (2020) found that task-fit, which has a conceptual similarity to UPE (Venkatesh et al., 2003), influences the ATT of individuals and BI to adopt technology. According to Zhao and Bacao (2020) services providers must ensure that the utilitarian aspects of technology meet the needs of individuals in various contexts.

5.2.4 HYPOTHESIS 2c

This study found that ATT toward using chatbots in the South African financial services industry positively mediates the relationship between HPE and BI to use chatbots which corresponds with the findings by Khalilzadeh, Ozturk and Bilgihan (2017). This study demonstrated that including the ATT construct in the conceptual model becomes significant when considering its effect on HPE (Khalilzadeh, Ozturk & Bilgihan, 2017). Notably, South Africans have a positive ATT towards using chatbots in the financial services industry and think it would be a pleasant experience to use them.

5.2.5 HYPOTHESIS 2d

Most researchers are of the belief that the relationship between UPE and BI is indirect (Zhang, Zhu & Liu, 2012). Nonetheless, this research found that ATT toward using chatbots in the South African financial services industry positively mediates the relationship between UPE and BI to use chatbots. An individual's ATT and their BI to use technology, may be shaped by the ease of use, or the utilitarian aspects of that technology (Dwivedi et al., 2019). Adopting technology often involves a change in behaviour, so there must be perceived benefits to justify adoption (Chan et al., 2022). Baptista and Oliviera (2015) emphasized that individuals consider the utilitarian aspects of technology to be important in their decisions to adopt technology.

Additionally, this study found that the relationship between UPE and the BI to use chatbots decreases when the inclusion of ATT is considered, and therefore confirming the mediation role of ATT. An individual's ATT and BI to use technology relies on the rational, utilitarian justification of performance expectations (Chan et al., 2022).

And therefore, consistent with Khalilzadeh, Ozturk and Bilgihan (2017) and Dwivedi et al. (2019) ATT towards technology plays a central role in the BI to use technology, and that ATT mediates the effect of performance expectancy.

5.2.6 HYPOTHESIS 3a

The results of this study found that the PR of using chatbots in the South African financial services industry indeed has a direct negative impact on PS. Although there seems to be improvements being made by service providers to address potential risks and security threats (Chao, 2019) this result is not surprising because there are still risk perceptions associated with new innovations (Chan et al., 2022).

There are security concerns that come with technology adoption, such as information security concerns and data sharing concerns (Chan et al., 2022). Perceptions of risk not only influence trust, but security aspects of technology as well (Khalilzadeh, Ozturk & Bilgihan, 2017).

Li et al. (2019) also confirmed that when individuals perceive the risk of using technology to be high, they hold a negative ATT towards the technology and in turn, are unlikely to use that technology. Although the study by Li et al. (2019) is based on mobile payment technology, this view might be extended to chatbots in the South African financial services as well.

5.2.7 HYPOTHESIS 3b

This study found that the PR of using chatbots in the South African financial services industry has a direct negative impact on PT. Compared to other constructs of the conceptual model, the effect of PR in the overall model proved to be more significant. Individuals have concerns about the privacy of their information when it comes to technology use (Khalilzadeh, Ozturk & Bilgihan, 2017). Managing the risk that comes with chatbots should be crucial for financial services providers. To ease the PR concern, individuals would be more comfortable engaging with reputable financial services providers that have a good reputation of safeguarding the privacy of information and mitigating risks for chatbot users (Chan et al., 2022).

Given that financial services providers perform functions that involve the finances of individuals and rely on exchanging of financial information (Chan et al., 2022), the significance of the PR effect in the research results is not surprising. However, when considering that this study is based on the adoption decisions of South Africans, the influence of cultural contexts should not be ignored. As such, the high effect of PR should not be taken as universal as the results could differ in other contexts.

5.2.8 HYPOTHESIS 3c

This study found that the UPE of using chatbots in the South African financial services industry negatively mediates the relationship between PR and HPE.

Yang (2010) affirmed that testing the relationships for HPE and UPE as separate constructs offers better explanatory strength than testing a single construct for PE as theorised in UTAUT.

Similarly, Khalilzadeh, Ozturk & Bilgihan (2017) found a negative relationship between PR and HPE, positing that the more individuals are concerned about their privacy when it comes to the performance of technology (i.e., utilitarian aspects), the less they will enjoy using that technology. Li et al. (2019) also found that risk perceptions have a negative effect on usefulness and ease of use (represented by UPE).

5.2.9 HYPOTHESIS 4

This study found that UPE in using chatbots in the South African financial services industry has a direct positive impact on the HPE of chatbots. The usefulness of the technology is directly impacted by level of fun and enjoyment that individuals experience from using technology (Khalilzadeh, Ozturk & Bilgihan, 2017). If individuals consider the utilitarian aspects of technology to be enjoyable, a feeling of satisfaction is created, which ultimately leads to them adopting that technology (Baptista & Oliviera, 2015). Useful experiences with technology lead to the enjoyment of using that technology.

There is another perspective to consider between UPE and HPE. Chatbots learn by experience, and so by answering similar queries multiple times, chatbots could sometimes fail to fulfil the intended tasks (Shah, Warwick, Vallverdú & Wu, 2016) which in turn would make the individual's experience less enjoyable. The best way for businesses to guard against chatbots failing to fulfil task performance is to ensure that chatbots incorporate a list of statements made to it into its memory (Shah et al., 2016). In that way, the chatbot becomes an ever-learning, ever-evolving business solution. that individuals enjoy using.

5.2.10 HYPOTHESIS 5a

This study found that ATT toward using chatbots in the South African financial services industry positively mediates the relationship between PS and BI to use chatbots. This result is consistent with the study by Khalilzadeh, Ozturk, and Bilgihan (2017) which revealed that ATT is the strongest determinant of BI to use technology, followed by PS and PR.

5.2.11 HYPOTHESIS 5b

In line with the findings by Shin (2009) and Khalilzadeh, Ozturk and Bilgihan (2017), this research validates the positive relationship between SI and PS. Individuals place importance on the opinions of their social circles, and experts around them. Individuals may rate the security of a technology based on the opinions of others (Khalilzadeh, Ozturk & Bilgihan, 2017). This may suggest that the adoption of technology may be increased through convincing others who are vital in a social circle (Talukder et al., 2020).

5.2.12 HYPOTHESIS 6

This study found that an individual's SE perceptions do not affect the amount of EE in learning and using chatbots in the South African financial services industry. The insignificance of SE perceptions on EE is not surprising in the context of chatbots, because with the popularity of the internet and technology developments in the digital era, individuals have high technology SE (Chao, 2019). And since the ability to use chatbots is simple, individuals are likely to interact with chatbots without requiring much learning effort (Lu, Cai & Gursoy, 2019).

The findings by Leong et al. (2013) are aligned with this study as well, citing that perhaps the insignificance of SE perceptions could be justified by the widespread of technology. It is noteworthy however, that individuals who believe they do not have the ability to use technology will not make the effort to learn the technology (Compeau & Higgins, 1995). Instead, they will avoid using the technology.

Conversely, Maillet, Mathieu and Sicotte (2015) found a positive effect of SE on EE, albeit weak. This result was attributed to the research design employed in the study because technology adoption was assessed at different adoption stages.

5.2.13 HYPOTHESIS 7a

PS of chatbots in the South African financial services industry was found to predict PT positively and directly. Shin (2009) emphasized the role of PS and trust in technology adoption.

While security and trust are known to be important considerations for individuals, firm reputation primarily drives the perceptions of security, risk, and trust (Chan et al., 2022). This means that trusted and reputable financial services providers that have chatbots are more likely to have an advantage compared to their competitors. Financial services providers should leverage their reputations to increase the level of security and trust perceptions among individuals.

5.2.14 HYPOTHESIS 7b

The results of this study found PT in chatbots in the South African financial services industry directly increases the amount of EE tolerance individuals need to continue learning and using chatbots. This result is consistent with the findings by Khalilzadeh, Ozturk & Bilgihan (2017) indicating that the effort that individuals put in to learning about technology increases the trust perceptions associated with that technology. If financial services providers deliver on their promises, individuals are more likely to put in efforts to learn about chatbots and to understand them better, and in turn, continue using chatbots.

Trust, in this context, is concerned with the belief that a financial services provider will ensure that a chatbot fulfils a request as expected (Wu & Chen, 2005). In this study, respondents indicated that they believe financial services providers in South Africa will indeed keep their promises and interests in mind. Zhou (2012) indicated that individuals expect that service providers will keep their promises and employ the necessary efforts and resources to ensure that.

5.2.15 HYPOTHESIS 7c

This study found that PT in chatbots in the South African financial services industry positively and directly predicts the BI to use chatbots. Studies have shown that considerations of trust and security are important factors in technology adoption (Shin, 2009). Pillai et al. (2022) argued that when individuals experience a higher level of trust from using technology, they are more likely to continue using it. The study results show that individuals believe that financial services providers will do everything to secure the details of their queries, and in turn, their BI to use chatbots will increase.

Chao (2019) also found a significant relationship between PT and BI citing that knowledge and awareness of technology increases an individual's trust in the technology, and in turn, the BI to adopt that technology. Interestingly however, Wong et al. (2020) found that PT has an insignificant effect on BI and attributed this result to a lack of knowledge about the technology.

5.2.16 HYPOTHESIS 7d

The more individuals worry about the trustworthiness of the technology, the less they will enjoy using it (Khalilzadeh, Ozturk & Bilgihan, 2017). This study found that PT for chatbots in the South African financial services industry positively impacts HPE.

Leong et al. (2013) found HPE to be a significant driver of technology adoption, while Shin (2009) emphasized the importance of trust in technology adoption. Individuals are keen on adopting chatbots if they are trustworthy (Simonite, 2017) and provided that the chatbot is entertaining and enjoyable to use.

5.2.17 HYPOTHESIS 7e

This study found that PT for chatbots in the South African financial services industry positively impacts UPE. Perceptions of trust, risk and security are often viewed together (Li et al., 2019). If individuals find that the services provided by technology are untrustworthy and unfit for their needs, they will perceive these services to be of low usefulness and, therefore, individuals will form low UPE about the technology (Zhou, Lu & Wang, 2010).

5.2.18 HYPOTHESIS 8a

The direct impact of SI of accepting chatbots in the South African financial services industry on the BI to use chatbots is significant, implying that the opinions of other people about the use of chatbots is important in the adoption of chatbots.

This result is consistent with the study conducted by Yang (2010) in which the relationship between SI and BI was proven. Yang et al. (2012), De Luna et al. (2019), and Khalilzadeh, Ozturk and Bilgihan (2017) also found that influences from friends, colleagues, and important social circles are determinants of technology adoption, although Khalilzadeh, Ozturk and Bilgihan (2017) found it to be weak.

In as much as Alwabel and Zeng (2021) also validated the positive impact of SI on BI, the study found that when ranked in order of importance, UPE and hence the usefulness associated with technology is more important than the opinions of social circles and influences.

Conversely however, Lu, et al. (2019) found that SI does not positively affect BI to adopt chatbots. This result is noteworthy, especially considering that Lu et al. (2019) and this study studied the same type of technology.

5.2.19 HYPOTHESIS 8b

This study found that the SI of accepting chatbots in the South African financial services industry directly and positively impacts HPE related to chatbots, although it was quite moderate. This result is consistent with Khalilzadeh, Ozturk and Bilgihan (2017) who indicated that even if individuals find technology to be entertaining and fun, they are more likely to adopt usage if their social circle supports the adoption of that technology.

Interestingly, Yang (2010) found that the enjoyment and entertainment aspects of technology, represented by HPE, is more critical than utilitarian aspects.

5.2.20 HYPOTHESIS 8c

This study found that the SI of accepting chatbots in the South African financial services industry directly and positively impacts UPE related to chatbots. Strong SIs appear to motivate individuals to adapt their utilitarian perceptions (Blut, Wang & Schoefer, 2016). Without the social support and influence to adopt technology, some individuals might exhibit less confidence to use technology (Blut, Wang & Schoefer, 2016). As such, some individuals might deem technology useless to them.

Individuals hold the opinions of those close to them in high regard (Venkatesh et al., 2003). The more people use chatbots in the South African financial services in society, the more other individuals will perceive it to be useful. The study result is consistent with the findings by Yang (2010) and Khalilzadeh, Ozturk and Bilgihan (2017) also having found a positive relationship between SI and UPE, however emphasized that hedonic aspects of technology are more salient than utilitarian aspects of performance expectancy.

An interesting assertion was also made by Chan et al. (2022) stating that individuals may tend to adopt technology not simply based on the support of their social circles, but also on seeing many others adopting that technology. Seeing several other people using technology might signal the utilitarian benefits of the technology, which therefore could affect the adoption (Chan et al., 2022).

And intriguingly, Alwabel and Zeng (2021) indicated that when considering SI and UPE independently, as two separate constructs, individuals regard utilitarian performance expectations of technology more important than the opinions of their social circles.

5.3 MODERATION DISCUSSION

5.3.1 HYPOTHESIS 9

Understanding the moderating effects of gender, age and previous experience provides insight on how demographics and technology experience affects the adoption of technology. This study found that four of the five BI paths are statistically significant for both males and females, with the only insignificant path being FC -> BI. The effect of SI on BI revealed a lower path coefficient for females compared to males. This finding contrasts to the proposition of the UTAUT which argued that women tend to be more sensitive to the opinions of others and might find SIs to be more salient in BI to adopt technology (Venkatesh et al., 2003).

Notably, and in line with the findings by Venkatesh and Morris (2000), this study found that males are greatly affected by ATT towards the adoption of technology, with a higher effect in comparison to females. This indicates that males have a more positive ATT towards chatbots and are of the belief that using chatbots is a wise idea.

The SI -> BI path is more significant for younger people, aged 18 – 35, compared to those aged 36 and above. Seemingly, younger people are encouraged by influences from their social circles more easily in comparison to older people (Leong et al., 2013). An interesting perspective on SI was highlighted by Leong et al. (2013) asserting that SIs in younger people do not just emanate from close family and peers, but from mass media influences too. On the other hand, the SI -> BI path was insignificant among the elderly (aged 45 and above), which may be attributable to the anxiety that comes with using technology (Talukder et al., 2020).

5.4 CHAPTER SUMMARY

In summary, this chapter revealed that the conceptual framework underpinning this study explains the indirect and direct effects of the factors that affect the adoption of chatbots in South Africa. Table 5-01 summarises the results discussed in this chapter.

Table 5-01: Summary of results

Hypothesis	IV	DV	Mediating variable	Moderating variable	Explanation
H1	FC	BI	-	-	Effect is weak in the conceptual model, and insignificant for males and females
H2a	EE	HPE	ATT	-	Effect is moderate
H2b	EE	UPE	ATT	-	Effect is significant in the conceptual model and stronger compared to HPE
H2c	HPE	ATT	BI	-	Mediated effect is moderate
H2d	UPE	ATT	BI	-	Mediating effect is strongest compared to other mediating hypotheses
H3a	PR	PS	-		Strong, direct negative effect
H3b	PR	PT	-		Moderate, direct negative effect
H3c	PR	UPE	HPE	-	Significant, yet weak mediating effect
H4	UPE	HPE	-	-	Significant and strong direct effect
H5a	PS	BI	ATT	-	Strong mediating effect exists
H5b	SI	PS	-	-	Significant direct effect
H6	SE	EE	-	-	Rejected from the research model
H7a	PS	PT	-	-	Significant, direct effect exists
H7b	PT	EE	-	-	Weak, direct effect exists
H7c	PT	BI	-	-	Effect is significant in the conceptual model and for previous chatbot users, younger users, and both males and females
H7d	PT	HPE	-	-	Direct effect is significant, stronger than UPE
H7e	PT	UPE	-	-	Direct effect is significant
H8a	SI	BI	-	-	Direct effect is significant
H8b	SI	HPE	-	-	Direct effect is significant
H8c	SI	UPE	-	-	Direct effect is significant

Source: Author’s explanations

6 CHAPTER 6. CONCLUSIONS AND RECOMMENDATIONS

6.1 INTRODUCTION

This chapter concludes this study. Firstly, a summary of the results of this study will be discussed, followed by policy and managerial implications based on the results of this research. The limitations of this study are also highlighted, followed by the suggestions for future research.

6.2 SUMMARY OF RESULTS

The rise in AI chatbots has created quite a buzz in the recent years, the launch of ChatGPT, Bing Chat and Google Bard has only just increased the popularity of chatbots. This study applied a research model that integrated the UTAUT constructs, ATT from TAM, SE construct, and security-related constructs to determine the factors that affect the adoption of chatbots specifically in the South African financial services industry. Data was collected from 440 individuals, and the data was confirmed to have high internal consistency and reliability, and therefore indicates that the conceptual framework offers high explanatory power.

From the effect sizes computed in Chapter 4, research objective (i) and (ii) was addressed as this study revealed that UPE, PT, ATT, SI, PR, and PS, are significant factors that affect the adoption of chatbots in the South African financial services industry. Not surprising, the effect of PT on BI is higher than the effect of SI, indicating that individuals value the trustworthiness of chatbots, more than being socially accepted for using chatbots.

On the other hand, SE was revealed to have an insignificant effect on chatbot adoption, demonstrating that self-perceptions about the ability to perform a task using technology are not important to individuals in South Africa. The effects of HPE, EE, and FC are revealed to be moderate. However, financial service providers should not ease efforts to make chatbots enjoyable to users because individuals are prepared to spend money on technology that brings them joy and entertainment (Leong et al., 2013).

To address research objective (iii), age, gender, and previous chatbot experience were revealed to moderate the BI paths only partially in the conceptual model proposed in Figure 1 and Figure 2, with some paths being significant and some being insignificant. The moderating hypothesis assessing the effects of gender, age and previous experience represented by H9 have a common theme that the FC -> BI path is insignificant across all genders, all age groups, and experience. However, since the research instrument was not invariant regarding previous experience, age, or gender, the result needs to be interpreted cautiously.

6.3 POLICY AND MANAGERIAL IMPLICATIONS

Perceptions of security, risk and trust emerged as quite significant factors affecting the adoption of chatbots in the South African financial services industry. From a regulatory framework perspective, requirements for data protection, security, and privacy associated with chatbots could be made more robust in the existing Protection of Personal Information Act in South Africa. And in organisational contexts, businesses could implement robust security measures when developing and deploying chatbots. Robust security measures could ensure the data protection and information security of individuals using the chatbot technology.

Organisational policies are instrumental to the adoption of technologies (Wong, et al., 2020), and as such, service providers should leverage feedback loops or mechanisms through which individuals can provide responses about their experience, and about their performance, security, and entertainment expectations.

To improve the ability of chatbots to successfully perform a task, businesses must ensure that chatbots have a constant feedback loop, and therefore creating an ever-improving coverage of possible instructions received from users (Shah et al., 2016).

Consumer education could also be prioritised by businesses that have adopted chatbots. Public awareness campaigns could be launched to educate individuals on the usage, benefits, and limitations of chatbots.

6.4 LIMITATIONS OF THE STUDY

This study was a cross-sectional study based on data collection at a point in time, which means that interpretation and inferences made in this study should be cautiously interpreted. Additionally, the respondents of this study are based in South Africa and the research context was specific to the financial services industry. As such, the results of this study should not be taken as universal because different results could be revealed in different contexts.

6.5 SUGGESTIONS FOR FUTURE RESEARCH

This study employed a quantitative approach with close-ended questions, although several studies have employed this same research approach to investigate technology adoption, a suggestion for future research is to explore a qualitative research design. A qualitative research design that employs open-ended questions and content analysis could reveal more complex motivational factors that influence the adoption of a novel technology (Liang, Eccarius & Lu, 2019).

Another suggestion for future research, is that a theoretical framework based on actual, real-world conditions could be more appropriate to explain the actual operations and adoption intentions of a novel technology.

Future research could also adopt a longitudinal research methodology, in that manner, richer insights could be revealed on how individual's BI to adopt chatbots changes over time (Zhou, Lu & Wang, 2010). A longitudinal study would also allow for researchers to corroborate the robustness of relationships evaluated in this study and to confirm the evolution of BI to use technology over time (Liébana-Cabanillas, Molinillo & Ruiz-Montañez, 2019).

Conducting this study in a more technologically mature country could be explored as well. Future researchers could examine if the results of this study would be consistent if applied in other countries regarding chatbot adoption.

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8 APPENDIX A: CONSISTENCY TABLE

The below consistency table summaries research objectives, hypothesis, data collection and data analysis, employed in this study.

<table>
<tr><th>Research objective no.</th><th>Research objective</th><th>Hypothesis no.</th><th>Data collection detail/item(s) on survey</th><th>Data analysis method</th></tr>
<tr><td>(i)</td><td>To investigate whether FC, ATT, PR, EE, UPE, PS, SE, PT, SI, and HPE are factors that affect the adoption of chatbots in the South African financial services industry.</td><td rowspan="2">H1, H2a, H2b, H2c, H2d, H3a, H3b, H3c, H4, H5a, H5b, H6, H7a, H7b, H7c, H7d, H7e, H8a, H8b, H8c</td><td rowspan="3">[FcCndn_1]
[FcCndn_2]
[FcCndn_3]
[FcCndn_4]
[ATT_1]
[ATT_2]
[ATT_3]
[ATT_4]
[PerfRisk¬_1]
[PerfRisk¬_2]
[PerfRisk¬_3]
[PerfRisk¬_4] [PrvcyRisk_1]
[PrvcyRisk_2]
[PrvcyRisk_3]
. [EffExp_1]
[EffExp_2]
[EffExp_3]
[EffExp_4]
[UtlPerfExp_1]
[UtlPerfExp_2]
[UtlPerfExp_3]
[UtlPerfExp_4]
. [Security_1]
[Security_2]
[Security_3]
[Security_4]
[SlfEffcy_1]
[SlfEffcy_2]
[SlfEffcy_3]
[SlfEffcy_4]
[Trust¬_1]
[Trust¬_2]
[Trust¬_3]
[Trust¬_4] [SocialInflnce¬¬_1]
[SocialInflnce¬¬_2]
[SocialInflnce¬¬_3]</td><td rowspan="2">Linear regression, correlations, ANOVA, and coefficient analysis. PROCESS macro for mediation hypotheses</td></tr>
<tr><td>(ii)</td><td>To assess if the aforementioned factors lead to an individual’s BI to adopt and use chatbots in the South African financial services industry.</td></tr>
<tr><td>(iii)</td><td>To ascertain if there is any evidence that age, gender, and previous chatbot experience are moderating factors driving chatbot adoption in the South African financial services industry.</td><td>H9</td><td>Firstly, split file into groups (gender, age, experience) and perform regression, ANOVA, and coefficient analysis.</td></tr>
</table>

Research objective no.	Research objective	Hypothesis no.	Data collection detail/item(s) on survey	Data analysis method
			[SocialInflnce¬¬_4] [HedPerfExp_1] [HedPerfExp_2] . [HedPerfExp_3] [BehIntent_1] [BehIntent_2] [BehIntent_3] [BehIntent_4]	

9 APPENDIX B: PARTICIPANT CONSENT

Dear Participant,

My name is Seolebaleng Priscilla Kedijang. I am completing my Master of Management in the field of Digital Business at the University of the Witwatersrand, Johannesburg. I am required to complete a research project, for which I have chosen the financial services sector in South Africa.

I am researching the "Factors that affect the adoption of chatbots in the South African financial services industry" under the supervision of Dr. C. Ndlovu.

I humbly request your assistance to enable me to complete my research in fulfilment of my studies by completing this questionnaire. Attached is a questionnaire that should take approximately 15 minutes to complete.

You are not required to provide your name, therefore your responses are anonymous. No personal identifying information will be collected. However, you must please give some demographic information, which is used only to establish patterns between different demographic groups. Your participation is entirely voluntary and you have the option to abandon the questionnaire at any point. Your participation involves no risk, penalty, or loss of benefits whether or not you participate. Please note that the findings of this study will be anonymously processed for academic purposes only.

The first part of the questionnaire comprises statements wherein you are required to rate the statements. Please select the appropriate options. The second part of the questionnaire captures demographic data.

Please feel free to contact me at 453509@students.wits.ac.za should you have any questions.

Regards,
Seolebaleng Priscilla Kedijang

I voluntarily agree to participate in this research. The research has been explained to me above and I understand what my participation entails. I agree that the findings of this study will be anonymously processed for academic purposes only.

10 APPENDIX C: UNIVERSITY OF THE WITWATERSRAND ETHICS APPROVAL

Graduate School of Business Administration
University of the Witwatersrand, Johannesburg

Wits Business School Ethics Committee
Constituted under the University Human Research Ethics Committee (Non-Medical)

Ethics Clearance Certificate

Ethics protocol number: WBS/DB453509/631

This certificate is only valid with a legitimate ethics protocol number and signed by the Researcher (below).

Project title	Factors affecting the adoption of chatbots: a South African financial services context
Investigator / Researcher	Ms Seolebaleng Priscilla Kedijang
Nature of Project	MM (Digital Business)
Decision of the Committee	Approved, provided stakeholders and participants are guaranteed anonymity and confidentiality.
Issue Date of Certificate	2023-01-04
Expiry date	Date of submission of the project / research report
Chairperson	Prof Anthony Stacey ☎ +27 11 717 3587 +27 82 880 4531 anthony.stacey@wits.ac.za

Declaration by Researcher

One copy must be signed by the Researcher and returned to the Chairperson of the Wits Business School Ethics Committee.

I fully understand the conditions under which I am authorized to carry out the abovementioned research and I guarantee to ensure compliance with these conditions. Should any departure to be contemplated from the research procedure as approved I undertake to resubmit the protocol to the Committee.

Signature

8 February 2023
Date:

11 APPENDIX D: UNIVERSITY OF THE WITWATERSRAND RESEARCH PERMISSION LETTER

UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG | **OFFICE OF THE DEPUTY REGISTRAR**

01 March 2023

Seolebaleng Priscilla Kedijang
Student Number (453509)
Master of Management
Wits Business School

TO WHOM IT MAY CONCERN

"Factors affecting the adoption of chatbots: a South African financial services context."

This letter serves to confirm that the above project has received permission to be conducted on University premises, and/or involving staff and/or students of the University as research participants. In undertaking this research, you agree to abide by all University regulations for conducting research on campus and to respect participants' rights to withdraw from participation at any time.

If you are conducting research on certain student cohorts, year groups or courses within specific Schools and within the teaching term, permission must be sought from Heads of School or individual academics.

<u>Ethical clearance has been obtained</u>. (Protocol number: WBS/DB453509/631)

<u>Research Expiration:</u> (Research submission date)

N Potgieter

Nicoleen Potgieter
University Deputy Registrar

Private Bag 3, WITS, 2050, South Africa | T +27 11 717 1204/9 | E nicoleen.potgieter@wits.ac.za | www.wits.ac.za
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12 APPENDIX E: RESEARCH INSTRUMENT

Construct	Survey question
FC	• I have the resources (e.g., internet, mobile device, laptop) necessary to use a chatbot in financial services. [FcCndn_1] • I have the knowledge necessary to use a chatbot in financial services. [FcCndn_2] • A chatbot in financial services is compatible with other technologies I use. [FcCndn_3] • I can get help from others when I have difficulties using a chatbot in financial services. [FcCndn_4]
ATT	• I like the idea of using a chatbot in financial services. [ATT_1] • I think that my ATT towards chatbots in financial services would be positive. [ATT_2] • I think that using chatbots in financial services is (would be) a wise idea. [ATT_3] • I think using a chatbot in financial services would be a pleasant experience. [ATT_4]
PR	• I think that the probability that something could go wrong with the performance of a chatbot in financial services is low. [PerfRisk_1] • I think a chatbot will always perform well and never create problems with my financial services query. [PerfRisk_2] • Considering the expected performance of a chatbot in financial services, for me to use it would be risky. [PerfRisk_3] • I would use chatbots in financial services if it is efficient. [PerfRisk_4]
PR	• In my opinion, the chances of using a chatbot in financial services and losing control over my personal information privacy are low. [PrvcyRisk_1] • I think using a chatbot in financial services would lead to my personal information being used without my knowledge. [PrvcyRisk_2]

Construct	Survey question
	• I think using a chatbot in financial services could expose my personal information to hackers. [PrvcyRisk_3]
EE	• Learning how to use a chatbot in financial services would be easy for me. [EffExp_1] • My interaction with a chatbot in financial services would be clear and understandable. [EffExp_2] • It would be easy for me to remember how to use a chatbot in financial services. [EffExp_3] • I would find a chatbot in financial services easy to use without asking for help. [EffExp_4]
UPE	• Using a chatbot would allow me to accomplish my financial services queries quickly. [UtlPerfExp_1] • I think chatbots in financial institutions could be useful to resolve my queries. [UtlPerfExp_2] • Using a chatbot enables me to accomplish things that are important to me in financial services. [UtlPerfExp_3] • Using a chatbot allows me to save time for my financial services queries/requests. [UtlPerfExp_4]
PS	• I would feel safe sending and receiving my information over a chatbot in financial services. [Security_1] • In my opinion, chatbots in financial services can easily be hacked. [Security_2] • I would feel safe providing sensitive information about myself over a chatbot. [Security_3] • I think my information would be safe while I use a chatbot in financial services. [Security_4]
SE	• I would prefer to use a chatbot in financial services if only there is a built in-help facility for assistance. [SlfEffcy_1]

Construct	Survey question
	• I would prefer to use a chatbot in financial services if there was someone, I could call for assistance. [SlfEffcy_2] • I would prefer to use a chatbot if someone else helped me to get started. [SlfEffcy_3] • I would prefer to use a chatbot if someone showed me how to use it first. [SlfEffcy_4]
PT	• I believe a financial services provider that uses a chatbot can keep their promise. [Trust_1] • I believe financial services providers that use chatbots keep customers' interests in mind. [Trust_2] • I believe financial services providers that use chatbots are trustworthy. [Trust_3] • I believe financial services providers that use chatbots will do everything to secure the details of a user's query. [Trust_4]
SI	• People who are important to me think that I should use a chatbot in financial services. [SocialInflnce_1] • People who influence my behaviour think that I should use a chatbot in financial services. [SocialInflnce_2] • People who are in my social circle think that I should use a chatbot in financial services. [SocialInflnce_3] • People whose opinions I value recommend that I should use a chatbot in financial services. [SocialInflnce_4]
HPE	• I think using a chatbot in financial services would be fun for me. [HedPerfExp_1] • I think using a chatbot in financial services would be enjoyable for me. [HedPerfExp_2] • I think using a chatbot in financial services would be entertaining. [HedPerfExp_3]
BI	• I intend to use a chatbot in financial services in the future. [BehIntent_1]

Construct	Survey question
	• I would increase my usage of a chatbot in financial services. [BehIntent_2] • I will always try to use a chatbot in financial services regularly in my daily life. [BehIntent_3] • I would recommend chatbots in financial services to others. [BehIntent_4]

13 APPENDIX F: ADDITIONAL RESULTS

Factor matrix (all measurement items – cross loadings and negative loadings)

	Factor										
	1	2	3	4	5	6	7	8	9	10	11
FcCndn_1	0.088	0.482	0.195	0.127	0.273	-0.086	-0.140	-0.215	0.168	-0.003	-0.043
FcCndn_2	0.131	0.659	0.190	0.264	0.223	0.038	-0.255	-0.184	0.187	-0.039	-0.050
FcCndn_3	0.217	0.515	0.198	0.116	0.314	-0.012	-0.188	-0.146	0.063	-0.030	-0.153
FcCndn_4	0.327	0.263	0.125	0.070	0.239	-0.068	-0.053	-0.096	-0.013	0.056	-0.076
ATT_1	0.786	0.012	0.145	-0.076	-0.074	-0.121	-0.199	0.043	-0.078	0.127	0.069
ATT_2	0.770	-0.019	0.123	-0.099	-0.052	-0.163	-0.283	0.020	-0.091	0.186	0.153
ATT_3	0.785	-0.029	0.158	-0.140	-0.024	-0.175	-0.215	0.030	-0.096	0.064	0.102
ATT_4	0.781	-0.070	0.117	-0.063	-0.061	-0.196	-0.193	-0.034	-0.131	0.073	0.067
PerfRisk_1	0.399	0.005	-0.169	0.039	-0.009	-0.066	-0.172	0.102	-0.169	0.173	-0.134
PerfRisk_2	0.461	-0.144	-0.177	0.035	-0.022	-0.096	-0.073	0.025	-0.045	0.218	-0.110
PerfRisk_3	-0.425	-0.184	0.103	0.096	0.216	0.091	0.192	-0.047	0.119	0.029	0.024
PerfRisk_4	0.451	0.070	0.099	-0.146	0.114	0.063	-0.146	-0.002	-0.022	-0.065	0.131
PrvcyRisk_1	0.427	0.189	-0.382	-0.171	0.026	0.093	-0.083	0.006	-0.035	-0.021	-0.120
PrvcyRisk_2	-0.319	-0.225	0.556	0.257	0.061	-0.110	0.079	-0.087	0.018	0.121	0.206
PrvcyRisk_3	-0.368	-0.226	0.509	0.233	0.064	-0.085	0.040	0.012	0.188	0.198	0.194
EffExp_1	0.229	0.550	0.259	0.100	-0.059	0.178	0.174	0.257	-0.109	0.170	-0.037
EffExp_2	0.464	0.425	0.168	0.052	-0.025	0.113	0.112	0.147	-0.090	0.200	-0.038
EffExp_3	0.392	0.546	0.185	0.094	-0.033	0.053	0.222	0.161	-0.068	0.028	0.100
EffExp_4	0.359	0.574	0.192	0.177	-0.064	0.128	0.281	0.107	-0.071	0.077	0.008
UtlPerfExp_1	0.674	-0.111	0.193	-0.027	-0.055	-0.170	0.071	0.266	0.182	-0.114	-0.162
UtlPerfExp_2	0.733	-0.066	0.278	-0.087	-0.079	-0.165	0.020	0.227	0.207	-0.135	-0.131

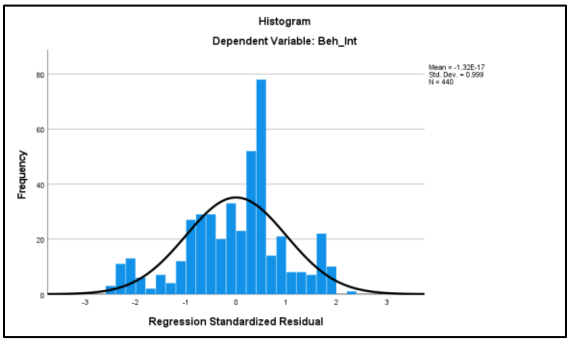
UtlPerfExp_3	0.782	-0.078	0.201	-0.070	-0.031	-0.116	-0.022	0.175	0.184	-0.130	-0.061
UtlPerfExp_4	0.706	-0.051	0.276	-0.072	-0.047	-0.098	-0.015	0.126	0.157	-0.166	-0.065
Security_1	0.617	0.145	-0.365	-0.138	-0.046	0.065	-0.039	0.075	0.057	0.036	0.134
Security_2	-0.363	-0.281	0.380	0.196	0.019	-0.088	0.045	0.006	0.050	0.087	-0.037
Security_3	0.520	0.057	-0.492	-0.066	0.068	0.137	0.054	-0.007	0.347	0.241	0.123
Security_4	0.600	0.134	-0.495	-0.152	0.041	0.150	-0.001	0.030	0.314	0.118	0.121
SlfEffcy_1	0.287	-0.023	0.198	-0.221	0.391	0.294	-0.051	0.089	-0.165	-0.143	0.122
SlfEffcy_2	0.161	-0.023	0.166	-0.244	0.477	0.331	-0.069	0.077	-0.125	-0.174	0.064
SlfEffcy_3	0.195	-0.524	0.126	-0.173	0.454	0.204	0.003	0.078	0.026	0.187	-0.118
SlfEffcy_4	0.236	-0.563	0.178	-0.165	0.390	0.096	0.002	0.100	0.049	0.168	-0.098
Trust_1	0.621	0.011	-0.267	-0.039	0.277	-0.255	0.234	-0.076	-0.081	0.020	0.030
Trust_2	0.633	-0.029	-0.037	-0.076	0.231	-0.315	0.271	-0.142	-0.127	-0.069	0.038
Trust_3	0.568	0.070	-0.263	0.018	0.383	-0.297	0.306	-0.067	-0.049	-0.019	0.017
Trust_4	0.602	0.021	-0.153	-0.018	0.151	-0.215	0.163	-0.041	-0.008	-0.028	0.024
SocialInflnce_1	0.551	-0.229	-0.162	0.555	0.076	0.077	-0.046	0.014	-0.008	-0.040	0.001
SocialInflnce_2	0.608	-0.234	-0.241	0.608	0.067	0.063	-0.082	0.086	-0.101	-0.104	-0.036
SocialInflnce_3	0.560	-0.206	-0.166	0.564	0.003	0.121	-0.055	0.057	0.012	-0.038	0.085
SocialInflnce_4	0.626	-0.236	-0.185	0.579	0.071	0.079	-0.048	0.046	-0.061	-0.054	-0.016
HedPerfExp_1	0.785	-0.116	0.184	-0.101	-0.187	0.159	0.072	-0.253	-0.044	0.093	-0.146
HedPerfExp_2	0.793	-0.136	0.194	-0.082	-0.216	0.168	0.094	-0.240	-0.045	0.094	-0.158

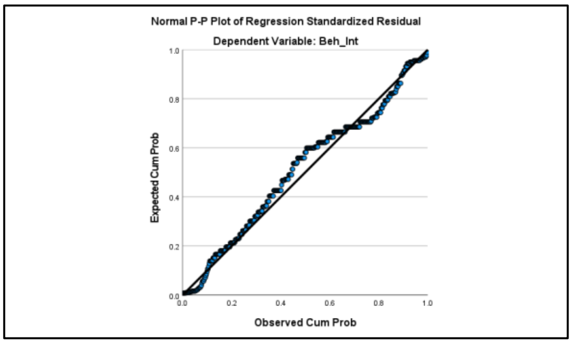
HedPerfExp_ 3	0.728	-0.204	0.119	0.022	-0.141	0.175	0.133	-0.255	0.018	0.056	-0.141
BehIntent_1	0.786	-0.043	0.174	-0.080	-0.148	0.091	0.007	-0.073	0.011	-0.135	0.136
BehIntent_2	0.797	-0.087	0.148	-0.057	-0.112	0.099	0.078	-0.134	0.050	-0.140	0.129
BehIntent_3	0.736	-0.141	0.123	-0.007	-0.152	0.220	0.115	-0.072	0.021	-0.054	0.046
BehIntent_4	0.803	-0.071	0.091	-0.031	-0.182	0.095	0.018	-0.127	0.010	-0.083	0.092
Extraction Method: Principal Axis Factoring.											
a. 11 factors extracted. 11 iterations required.											

Source: Author's calculations

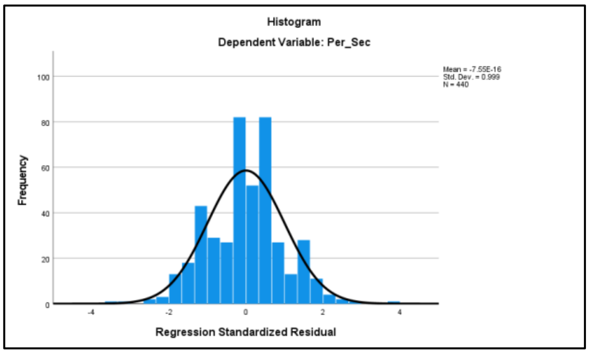
Figure 5: Histograms, normal p-p plots, and scatterplots for linear regressions

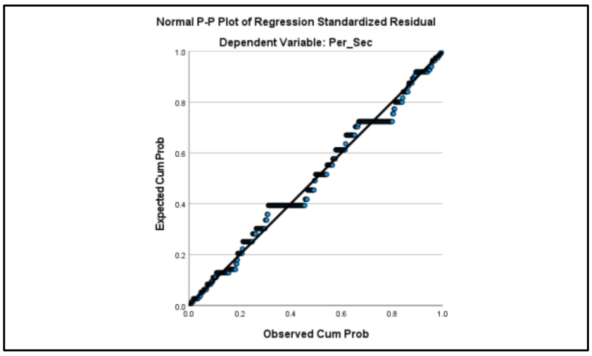
Hypothesis 1



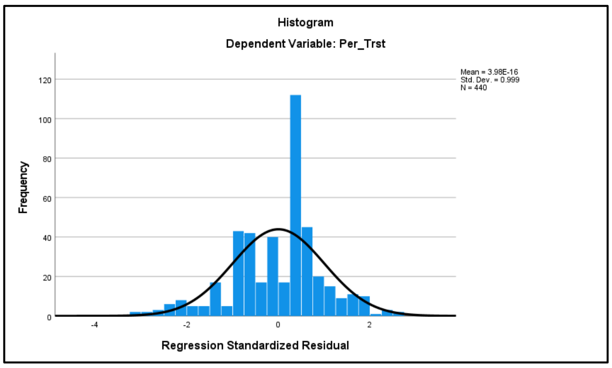


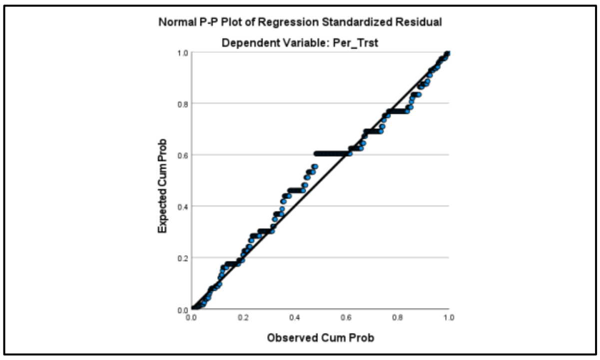
Hypothesis 3a



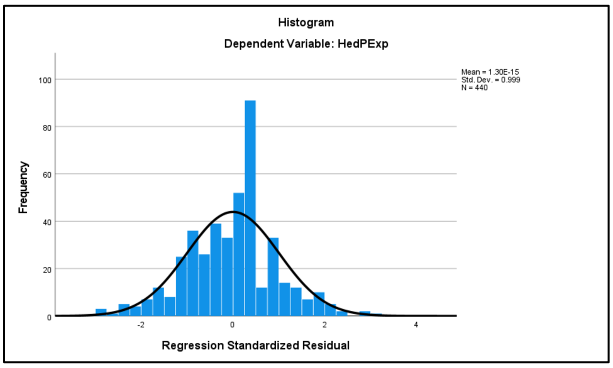


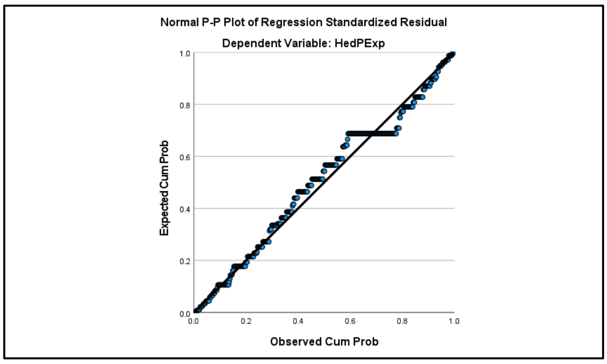
Hypothesis 3b



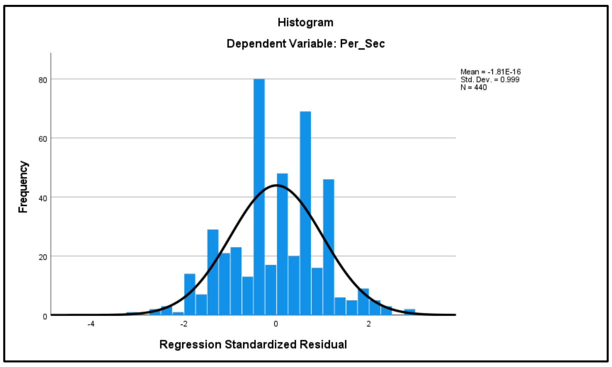


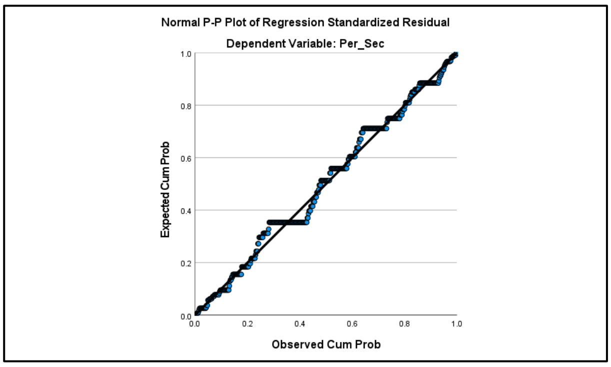
Hypothesis 4



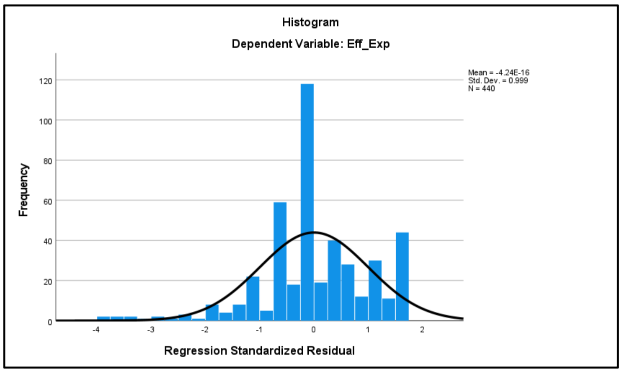


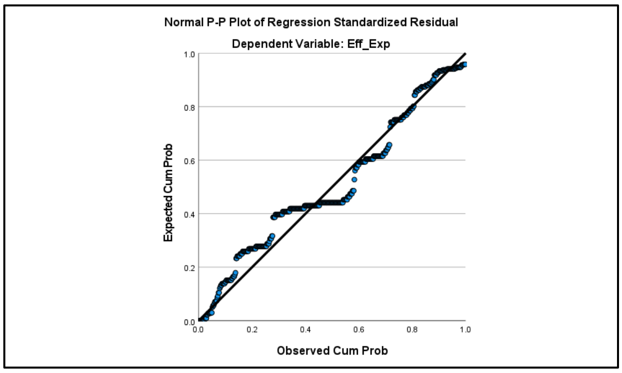
Hypothesis 5b



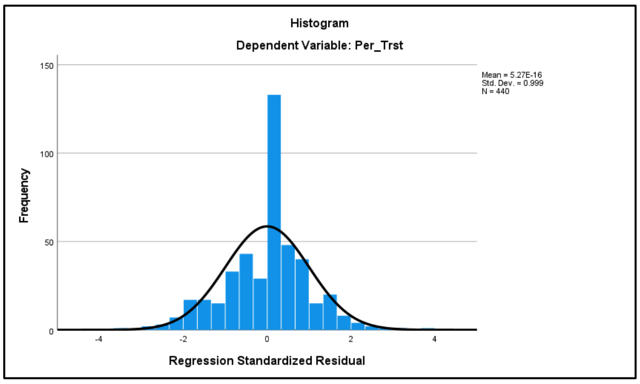


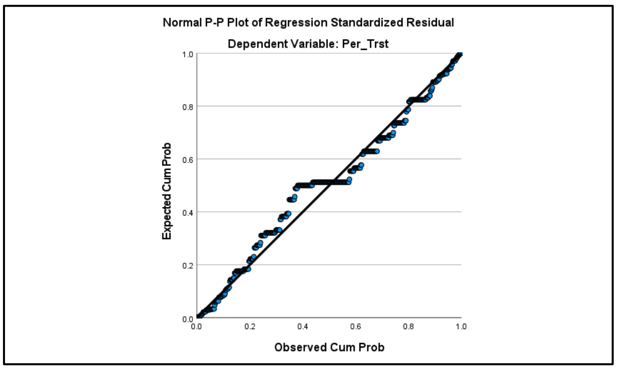
Hypothesis 6



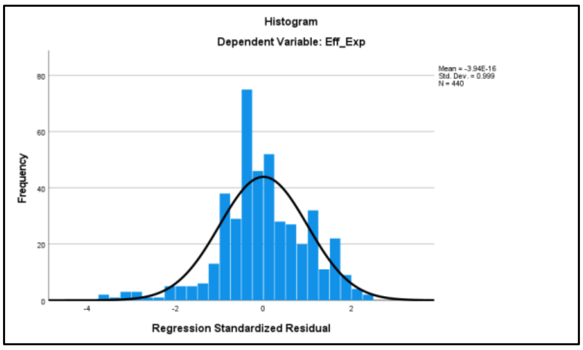


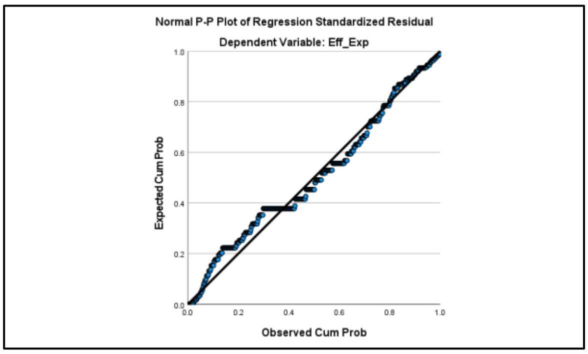
Hypothesis 7a



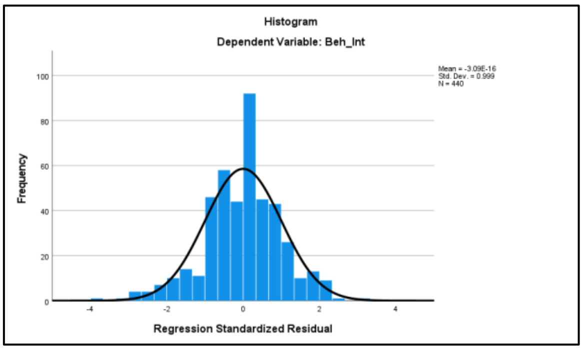


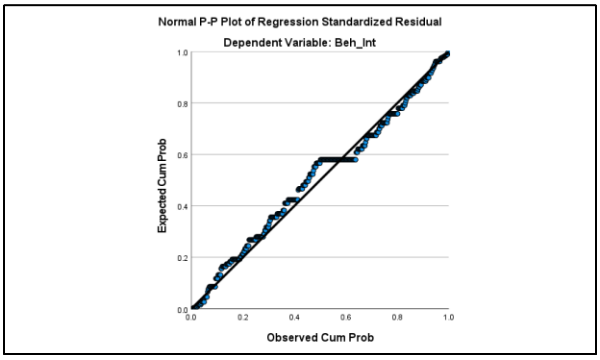
Hypothesis 7b



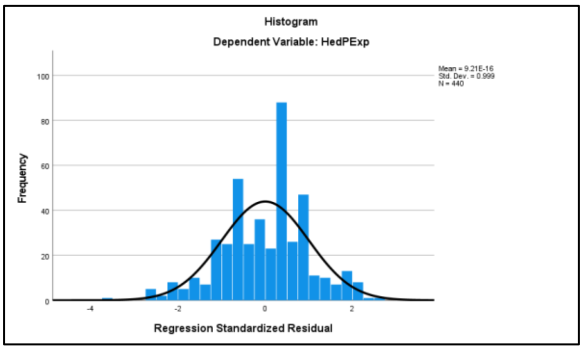


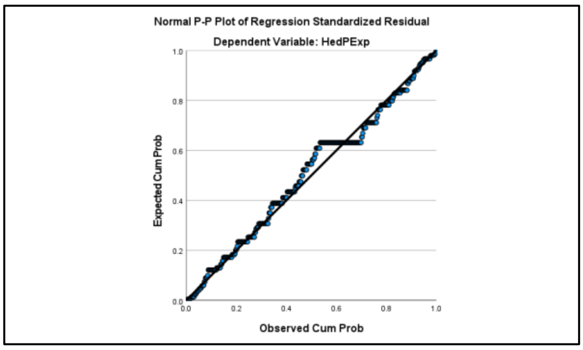
Hypothesis 7c



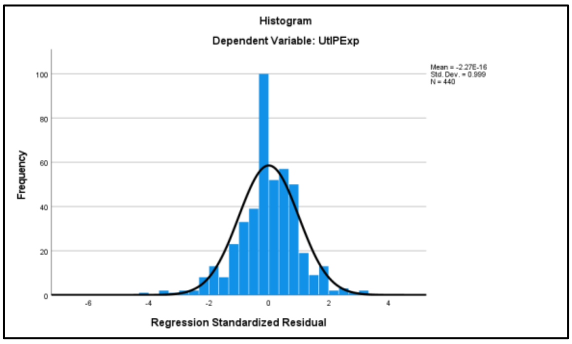


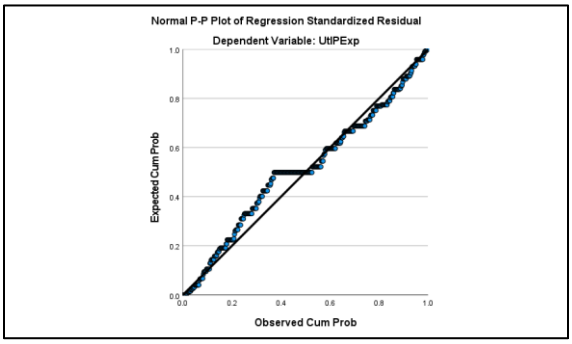
Hypothesis 7d



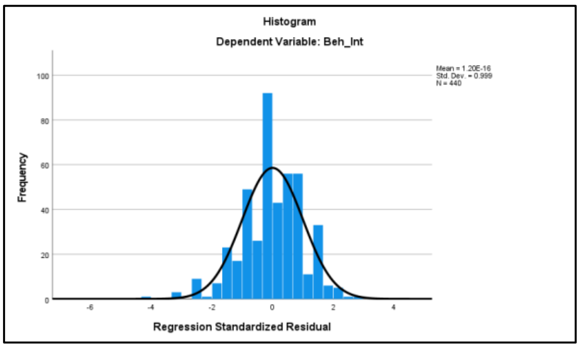


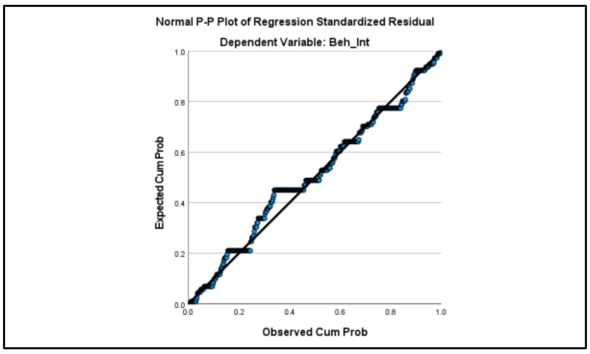
Hypothesis 7e



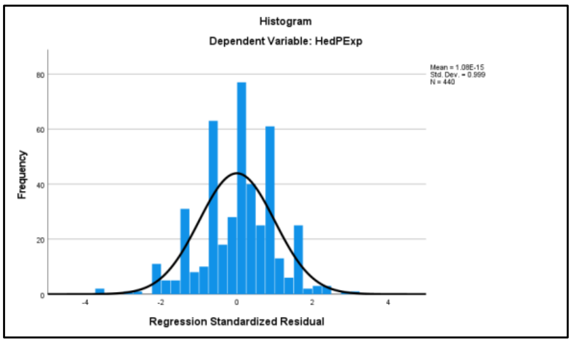


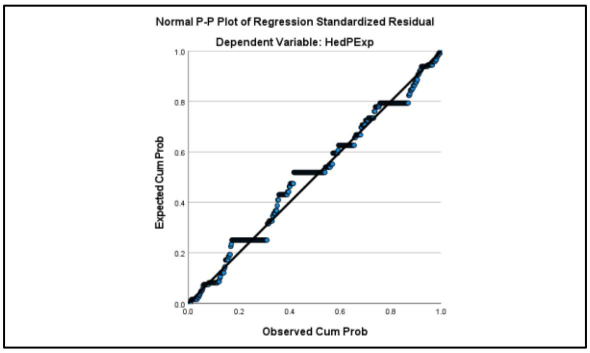
Hypothesis 8a





Hypothesis 8b





Hypothesis 8c