Gordon Institute of Business Science
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Inhibitors to the adoption of facial recognition payments.

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A research project submitted to the Gordon Institute of Business Science, University of Pretoria, in partial fulfilment of the requirements for the degree of Master of Business Administration.

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Abstract

Facial Recognition Payment Services (FRPS) are increasing in popularity globally, largely due to the convenience of the innovation. Existing literature has explored general consumer adoption of FRPS and resistance primarily relating to the privacy concerns the service introduces. This quantitative study explored potential inhibitors evident in consumers relating to the Use Intention (UI) and Intention to Recommend (ITR) as a payment service using Innovation Resistance Theory (IRT) as the core framework. Elements of the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT) and Status Quo Bias (SQB) theory were used to formulate the conceptual model. The study utilised an online survey to collect 303 consumer responses through a non-probability, snowball sampling methodology. Smart-PLS was then used to conduct Partial Least Squares Structural Equation Modelling (PLS-SEM) on the collected data. The research found that Usage, Risk, and Image Barriers are significant predictors of inhibition of Use Intention whilst Inertia and Mistrust significantly impede a consumer's intention to recommend FRPS. It was further noted that Desirability did display signs of moderation within the model.

Keywords

Facial Recognition Payment Systems, Biometric Payments, Inhibitors

Plagiarism Declaration

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

Student Number: 21752266
08 January 2024

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List of Abbreviations

Abbreviation	Description
ATM	Automated Teller Machines
CB-SEM	Covariance Based Structural Equation Model
EFT	Electronic Funds Transfer
EMV	Euro Master Visa (Card System)
FRP	Facial Recognition Payment/s
FRPS	Facial Recognition Payment Systems
HTMT	Heterotrait–Monotrait
IB	Image Barrier
IRT	Innovation Resistance Theory
ITR	Intention to Recommend
m-Government	Mobile Government
PLS-SEM	Partial Least Squares Structural Equation Model
RB	Risk Barrier
SEM	Structural Equation Model
TADU	Technology Adoption Decision and Usage
TAM	Technology Acceptance Model
TB	Tradition Barrier
TFI	Traditional Fit Index/Indices
UB	Usage Barrier
UI	Use Intentions
UTAUT	Unified Theory of Acceptance and Use of Technology
VB	Value Barrier

Table 1. List of Abbreviations

1. Chapter One: Introduction to the Research Problem

1.1. Introduction

This chapter introduces the research topic of the Inhibitors to the adoption of facial recognition payment systems (FRPS). The chapter will detail the research problem and the purpose of the research and highlight the value that will be derived from both a practical and theoretical perspective.

1.2. Background To the Research Problem

The progression of the internet and advancements in associated information technology have bolstered the growth and adoption of various non-cash and digital payment options in recent times (Tee & Ong, 2016). Numerous studies have presented the emergence of various non-cash, digital and contactless payment methods, such as credit and debit cards (Schuh & Stavins, 2011), mobile wallets (Aydin & Burnaz, 2016), e-wallets (Teoh Teng Tenk et al., 2020), mobile banking (A. S. Yang, 2009), near-field-communication payments (Pal et al., 2015), mobile payments (Dahlberg et al., 2015), quick response code payments (Lane et al., 2012), wearable payment technology such as Apple Pay via Apple Watch (Liébana-Cabanillas et al., 2020; Loh et al., 2022) which are becoming more widely accepted and adopted from both a consumer and business perspective. To support this trend, retailers and other businesses have adopted and implemented systems that can accept and process these cashless payment mechanisms within their environments, with the aim of optimising transaction efficiencies at checkout, minimising customer waiting times and ultimately optimising customer experience (Khalilzadeh et al., 2017; Lau et al., 2019; Leong et al., 2013).

Facial Recognition Payments Systems (FRPS) are an example of an emerging payment innovation being met with market resistance. In China, high levels of users' FRPS concerns are highlighted by Lee & Pan (2023), who demonstrate that perceived overload leads to high levels of technostress among users. Further research demonstrates users' concerns regarding privacy-related factors (Hu et al., 2023; Liu et al., 2021). In these studies, users are deterred from utilising FRPS due to perceived privacy risks emanating from using the payment innovation.

The Innovation Resistance Theory (IRT), the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) are all deemed to provide valuable frameworks that assist in articulating how these payment systems may be adopted or rejected in the market.

1.3. Theoretical Relevance of The Study

The proposed research paper focuses on facial recognition payments, which hold significant theoretical relevance in finance and technology. By studying the integration of facial recognition capability with payment systems, we can explore the potentially transformative impact it can have on how financial transactions are conducted. This paper examines the theoretical foundations of facial recognition technology, delving into its core principles, capabilities, and limitations. It further aims to investigate the theoretical implications of utilising facial recognition to facilitate a financial transaction whilst considering the users inhibition to adopt such a mechanism. Overall, the research paper aims to contribute to the theoretical understanding of consumer behaviour relative to the innovation that is unfolding within the biometric payment realm.

1.4. Business Rationale of The Study

The global facial recognition payment market is anticipated to grow to approximately US$7,2 million by 2027, indicating a compounded annual growth rate of 17,2% between 2022 and 2027 (IndustryARC, 2021). This growth positions FRPS as an emerging payment technology that drives numerous benefits for users, such as increased user convenience, enhanced safety and security, increased levels of user privacy, and faster checkout times (ARATEK, 2023). Whilst FRPS technology is still nascent, facial recognition technology's projected growth and potential make it an emerging technology with relevant business use cases. This research aims to provide insight for businesses such as banks, regulators, and technology service providers to enable data-driven insights and decisions concerning the adoption and enablement of FRPS technology across their relevant business spheres.

1.5. Problem Statement & Research Question

Businesses across the globe need to adopt payment acceptance technologies that their customers will utilise. FRPS is one such technology that will be rolled out to various environments, but the challenge faced in consumer adoption is still a concern. Research is required to understand further factors influencing a user's propensity to utilise FRPS as a service.

Existing research focuses mainly on privacy concerns relating to FRPS, which, whilst valid, does not account for other influencing factors such as the technology's physical, economic, functional, and social aspects.

These influencing factors contributed to the formulation of the study's primary research question;

How, and to what extent, is a user’s intention to utilise and recommend FRPS as a service inhibited by perceptions, opinions, and prepositions of facial recognition technology?

1.6. Research Aim: Theoretical & Academic Contribution

The primary contribution of this research is to provide insight into the inhibiting factors of users adopting FRPS as a primary mode of payment. The proposed FRPS study will contribute to the fields of technology, finance, and user experience by utilising appropriate theoretical frameworks. By investigating the inhibitors of consumer adoption concerning FRPS, the study will offer valuable insights into the potential benefits and possible challenges of this emerging payment method. The research findings can inform regulators, policymakers, financial institutions, fintech and other technology institutions about the viability of implementing FRPS at scale. Furthermore, the study can be used to shed light on user acceptance and resistance regarding facial recognition technology, thus guiding and shaping the future of FRPS systems. Ultimately, the proposed research aims to contribute towards the body of knowledge in the FRPS realm and aid in advancing the understanding and practical implications of implementing FRPS as a valid payment process, potentially revolutionising how transactions are conducted across various channels and streamlining processes for individuals and businesses.

1.7. Research Aim: Business Contribution

The author aims to identify key relationships between the implementation of facial recognition as a digital payment and the inhibiting factors that would drive users to avoid adoption or oppose the use of the facial recognition payment system.
The research will aid businesses engaging in facial recognition payments understand the users' primary concerns with the technology and address them through their business models.

1.8. Structure of this Research Report

Chapter 1: Introduction to the Research Problem
This chapter provides background to the study and articulates the intent of the study and highlights the research aim from an academic and business perspective.

Chapter 2: Literature Review
The second chapter outlines existing literature pertaining to Facial Recognition Payment Services and applies theoretical frameworks based on technology adoption and resistance to technology adoption. The hypotheses are presented based on the reviewed literature in this chapter.

Chapter 3: Conceptual Model, Research Questions and Hypotheses
The third chapter utilises the learnings from the second chapter to build out the conceptual model utilising the proposed hypotheses and theoretical frameworks.

Chapter 4: Research Methodology
The approach to the research is detailed in the fourth chapter. The research design, approach and considerations are outlined in detail.

Chapter 5: Research Findings and Results

The fifth chapter presents the findings from the statistical analysis and test performed on the collected data. The findings are validated and checked for reliability before presenting the outcome relating to the proposed conceptual model.

Chapter 6: Discussion of Results
In the sixth chapter, the findings in chapter 5 are relayed and positioned against the reviewed literature providing insight into the how the proposed hypotheses were received.

Chapter 7: Conclusion and Recommendations
The seventh and final chapter concludes with the overall learnings, followed by the identified limitations and recommendations for future research.

1.9. Conclusion to the Introduction

Chapter 1 highlighted the requirement for this research study in the context of FRPS. In terms of payment innovation, we note that FRPS has seen significant growth and adoption but is still met with resistance.
The limited research available in this field provides an opportunity to contribute to the learnings and builds onto existing theoretical models and frameworks.
The research problem is clearly framed and requires adequate attention to further the body of knowledge available.

2. Chapter Two: Literature Review

2.1. Introduction

This chapter reviews the literature of work completed in relation to the primary constructs of the proposed study, which are the inhibitors of biometric payment adoption. The review analyses both a user's intent to utilise and recommend an innovation post and pre-use and potential inhibitors to utilise and recommend the innovation. The chapter introduces the primary theoretical framework underpinning the study, the Innovation Resistance Theory (IRT), and the dependent variables, which include the intention to use the payment system. The chapter also introduces the moderating components used in the data collection and analysis phase.

Investment by firms in new technology is ever-increasing due to exponential growth and advancements in technology and information systems (Venkatesh et al., 2003). Understanding the factors behind what drives the successful adoption of technology would thus be deemed vital to continued, successful investment into technology and associated systems. Academic literature has successfully articulated various aspects of what drives users' adoption of technology, as illustrated by various insights into biometric payments. This research has primarily focused on the adoption of technology which utilises the Technology Acceptance Model (TAM) to understand what drives consumer acceptance of technology; however, a significant absence of academic literature that focuses on factors that may inhibit the adoption of Facial Recognition Payment Systems (FRPS) was noted.

The rapid evolution of payment technology methods means that retailers, banks, and other stakeholders in the payment value chain need to constantly improve product and service offerings to meet the demands of their customers (Moriuchi, 2021; Zhong et al., 2021). To understand and deliver products and services that meet the users' requirements, value chain participants should focus on delivering services and systems that will be adopted and utilised frequently to avoid building and deploying redundant systems (Mallat, 2007).

2.2. Literature Review – Facial Recognition Payment Systems

2.2.1. Biometric Systems

Biometric identification is defined as a technology-based process that relies on recognising an individual's unique physical traits to confirm their identity (A. K. Jain et al., 2006; Weaver, 2006). These traits include an individual's physiological traits such as fingerprints, iris patterns, hand and vein geometry, DNA analysis and facial feature recognition (Weaver, 2006). Biometric identification can extend into the analysis of behavioural traits, including voice patterns, gait analysis, mouse use characteristics, keystroke behaviour and signature analysis (Alzubaidi & Kalita, 2016).

A biometric system effectively recognises patterns in an individual's unique features and establishes the validity or authenticity of a specific physiological or behavioural characteristic displayed by the user (A. Jain et al., 2000).

2.2.2. Biometric Technology and Algorithms

Biometric literature dates back as far as 1870, when the biometric methodology of Alphonse Bertillon was utilised to measure the body parts of prisoners for identification purposes (Chapman, 1993). This rudimentary method of measurement considered a person's skull diameter and arm and foot length (Chapman, 1993) and has since evolved to a more precise analysis of biometric features utilising increasingly complex technologies.

The biometric analysis is essentially divided into two primary groups: Physiological, which includes the analysis of fingerprints, hands, iris, face, and DNA (Weaver, 2006) and Behavioural, which includes analysis of features such as voice, signature, keystroke, mouse use and even gait analysis (Alzubaidi & Kalita, 2016).

Most biometric systems deployed in real-world scenarios are unimodal; that is, they rely on a single source of identified information for authentication (Ross & Jain, 2004). These systems have the challenge of contending with an assortment of tribulations that a unimodal approach brings. These challenges could include noise in sensed data, such as a fingerprint with a newly healed scar or a voice that has been temporarily altered due to a cold (Ross & Jain, 2004). This noise could be amplified by poorly maintained identification equipment, such as a dirt and grease build-up on a fingerprint sensor, or unfavourable ambient conditions, such as poor lighting in a facial recognition environment (Ross & Jain, 2004).

The limitations introduced by unimodal systems can be countered by including multiple sources of identification information (Ross & Jain, 2003). These systems, otherwise known as multimodal biometric systems, have been shown to be more reliable than unimodal approaches due to the inclusion of multiple independent verification data sources (Kuncheva et al., 2000; Ryu et al., 2021). The validity of authentications stemming from using Multimodal biometric systems has further been strengthened by introducing deep learning and artificial intelligence systems (Ryu et al., 2021; Sengar et al., 2020).

2.2.3. Biometric Payment Systems

Consumer payment applications for biometric identification and authorisation currently include electronic funds transfer (EFT), in mobile or e-banking (First National Bank, 2023), online transactions in an e-commerce environment (Plateaux et al., 2014) as well as physical in-store card-based payments (Mastercard, 2021).

Leading companies in the payment sphere have conducted numerous projects to evaluate the safety aspects of biometric payments (American Express, 2019). Idemia, a technology services provider, has introduced various biometric authentication systems and launched a fully EMV-compliant biometric payment card that uses a user's fingerprints to authorise the payment (Idemia, n.d.). Mastercard has initiated a biometric card payment project that utilises this technology to allow users of their card payment systems to verify payments with their fingerprints (Mastercard, 2021). More recently, Visa has partnered with a Ukrainian technology partner to enable retail shops in Ukraine to utilise a biometric payment method which utilises facial recognition as its authentication means (Visa Navigate, 2021).

2.2.4. Facial Recognition Payment Systems

The introduction of facial recognition technology has allowed users to pay for goods and services by utilising a convenient new form factor in the form of Facial

Recognition Payments (FRP) (C. T. Lee & Pan, 2023). The Facial Recognition Payment Systems (FRPS) process is explained by Gao et al. (2020), where users simply need to present their faces to the camera on the self-checkout screen. When the option for FRP is selected, the user is verified and authorised, and payment occurs through a secure payment process using a registered store of value such as a debit or credit card account. FRP, as a payment method, should ideally include three primary or core elements to compete with existing payment methods (Vazquez-Fernandez & Gonzalez-Jimenez, 2016). According to (Vazquez-Fernandez & Gonzalez-Jimenez, 2016), these elements are (1) usability, which aims at driving a low false failure rate; (2) security, as the payments system must have the capability to prevent and/or reject fraudulent transactions; and (3) availability, meaning that a user of FRPS should be able to facilitate payment without being constrained by time factors.

As a payment type, FRP is one of many biometric payment form factors. Past studies have investigated various factors that could potentially influence the acceptance of biometric payment functionality. Significant barriers related to the acceptance of biometrics by users in the mobile banking realm include the drawbacks related to facial anti-spoofing and detection of whether the user was, in fact, live and present at the point of transaction (Goode, 2018). Concerns surrounding privacy, specifically relating to the use and storage of personal biometric data and lifecycle management issues, were further noted by (Goode, 2018).

By using FRP, individuals authenticate transactions by looking at their phone or computer instead of using one-time passwords or two-step verification. Facial recognition is safer as there are no passwords for hackers to compromise. Similarly, some automated teller machines (ATM) cash withdrawals and checkout registers can use facial recognition to approve payments (Amazon Web Services, 2023).

Kim et al. (2019) further stress that while mobile payments are becoming increasingly popular as a viable alternative to physical card-based payment processes, biometric payments are still at a relatively nascent stage. Some of the reasons underlying this slow adoption include the user's concern relating to the conceivable risks of sensitive, biometric information stored and utilised by financial institutions and doubts relating to the security protocols of the payment infrastructure such as the physical hardware used in the payment process.

2.2.5. Facial Recognition Adoption In Alternative Use Cases and Applications

Biometric identification and applications provide a host of use cases for users to verify their identity and authenticate a transaction or activity. Biometric authentication in the travel industry has previously relied on the identification of a person through their travel passport photo which introduces challenges such as subjective adjudication of the traveller, changes in facial profile, such as the growth or removal of facial hair in men (Chlond & Eisenmann, 2018). Biometric identification and authentication have already been implemented within the Dubai Airport which enables travellers to verify their identity and validate their authentication to enter the country with automated biometric systems (Emirates, 2022).

Many airports use biometric data as passports, allowing travellers to skip long lines and walk through an automated terminal to reach their gate faster. Face recognition technology in the form of e-Passports reduces wait times and improves security (Amazon Web Services, 2023).

2.2.6. FRPS Benefits and Advantages

Despite a lack of uniform regulations across facial recognition uses globally (Banisar & Davies, 1999; Bhaimia, 2018; Custers et al., 2018), the technology has presented a host of societal benefits ranging from traffic safety (Luo & Guo, 2021) to medical advancements (Jeon et al., 2019) to enabling payment technology (Palash et al., 2022).

Prior research has investigated users' opinions of FRPS and subsequent service adoption. There has been a notable increase in interest in the privacy trade-off in the context of FRPS. Liu et al. (2021) evaluated innovation resistance by incorporating the privacy calculus model. This study revealed that the perceived effectiveness of a robust privacy policy has a notable influence on privacy-related aspects such as perceived privacy risk and control of one's privacy.

Factors relating to system quality have been found to influence the user's intentions to engage in FRP. L.-L. Zhang et al., (2021) observed convenience, reliability, and security of FRPS as having a negative impact on user intention to engage in and utilise the service.
Numerous positive factors were identified by Zhong et al., (2021) through the application of a Technology Acceptance Model (TAM) as a theoretical framework. The research exposed factors such as perceived enjoyment, facilitating conditions, system availability, and ease of use as influential factors toward FRP system adoption.

Amazon Web Services (2023) positions FRP as a faster and more convenient payment service than other biometric technologies such as fingerprint or retina scanning. Amazon has demonstrated FRPS capabilities and have eliminated the need for physical check-out and payment processes (Amazon Staff, 2023). Facial recognition systems are adaptable and capable of supporting multifactor authentication which promotes additional security verification (Ross & Jain, 2004) as can be seen in the example of Amazon Go.

2.2.7. FRPS Challenges and Concerns

Facial recognition payment systems are not without their flaws. Since the introduction of facial recognition systems, there have been many challenges that the systems have faced.

Variable lighting conditions can significantly affect a person’s decipherable facial profile and subsequently affect the identification process (M. Singh & Arora, 2016).

A significant challenge with the pose was identified as a key concern and challenge with facial recognition and has been a focal point of research within the realm of facial recognition (X. Zhang & Gao, 2009).

Facial occlusion has also been deemed to be a significant issue with driving accuracy within facial recognition results (Sharma et al., 2013). When any portion of the face

is blocked or cannot be fully viewed by the system, authentication of the face is compromised, and the occlusion results in a negative outcome.
Hair can pose a challenge for facial recognition as it can cover important facial features such as the forehead, making it difficult to identify an individual (Wright & Sladden, 2003). Additionally, hairstyles, hair colour, hair length and facial hair can change frequently, further complicating the identification process (Toseeb et al., 2012). To address this issue, most facial recognition systems neutralise the impact of hair by disregarding it in the identification process (X. Li & Da, 2012). Further research and development is ongoing to solve this challenge.

Human expressions are natural occurrences often resulting from underlying emotions in an individual. Facial recognition systems can be affected by changes in human expression, which results from the movement of the individuals' facial muscles; this, in turn, leads to changes in facial images (Samadiani et al., 2019). Not all facial recognition systems can process changes in expressions by an individual, which could lead to identification challenges (X. Li & Da, 2012).

As individuals age naturally, facial features can undergo radical transformation, affecting the identification process of facial recognition systems. This area of research is still very much at a nascent stage and requires more attention to solve this problem (Abate et al., 2007).

The performance of biometric systems has been known to be affected by the user demographic (Council & Committee, 2010). Demographic factors have been shown to influence the speed and accuracy of numerous biometric systems authentication processes (Cook et al., 2019). Cook et al. (2019) found that relatively lighter-skinned individuals posted faster, more accurate authentication results than their darker-skinned counterparts. This was primarily attributed to the reflectiveness of light off the individuals' facial profiles.

2.2.8. Legal and Regulatory Framework

Whilst there has been a notable increased interest in consumer data protection globally, the legislation governing data privacy protocols is often complex, and laws are not aligned across governments (Custers et al., 2018; Mulligan et al., 2019).

2.2.9. Privacy and Ethical Considerations

The use of facial recognition, whilst convenient, is met with concern from users who consider the system impactful from a privacy and ethical perspective. Facial recognition systems adopted for use within m-government services delivery has seamlessly empowered governments to collect, store, process and utilise personal information relating to a human face (Ntaliani et al., 2008), including details relating to their gender, age, identity and in some instances, sexual orientation which users perceive as containing risk related to potential privacy leaks (Liu et al., 2021). Users additionally feel that there is a heightened level of futility in their efforts to protect their privacy and personal information (J. Yang, 2010). This psychological state of tiredness resulting from the feeling of futility can be viewed as a phenomenon known as privacy fatigue (Choi et al., 2018; J. Yang, 2010). Instead of actively protecting their data and maintaining a sense of privacy, fatigued users tend to engage in disengaged behaviours, manifesting as emotional enervation and pessimistic action about information protection and privacy threats (Choi et al., 2018). Lutz et al. (2020) note that increased privacy fatigue amongst users would decrease the overall effectiveness of digital engagement. Users' perceptions of institutional accountability, trust and satisfaction are further influenced (Lutz et al., 2020), creating a negative perception of governance amongst the users (Agozie & Kaya, 2021).

It could be argued that facial recognition technology has the potential to significantly transform our experiences of monitoring in a host of private and public arenas. However, with concerns about using facial recognition technologies in a free society increasing among groups, resistance to adopting the technology could be seen as a concern to service providers.

2.2.10. User Acceptance and Adoption of FRPS

Palash et al. (2022) found that relative advantage and privacy risk greatly influence the adoption and use of FRPS, while W. K. Zhang & Kang (2019) found that factors such as safety, security, visibility, and social image will affect a consumer’s intent to use the system.

While facial recognition technology can introduce various convenience and security measures, these systems generate, store and process copious amounts of personal information about individuals' movements, predilections, and associations (Raji et al., 2020), and it is this storage and use of data that has been shown to affect a user's intention to adopt and use FRPS

The past few years of academic research have surfaced numerous reports of facial recognition systems failing to recognise African American skin because of the racially skewed data sets that the algorithms have been built and trained on (Noble, 2018) as well as the failure of systems being unable to differentiate the facial recognition characteristics between identical twins (Paone et al., 2014). As a result of these flaws, there are concerns surrounding the misidentification of individuals at a personal level and a larger scale (Jacob Snow, 2018; Rapcsak, 2019), as well as machine bias in the form of systematic misidentification of individuals with specific skin colours or ethnic backgrounds (Crawford & Paglen, 2021).

2.2.11. Main Findings

Despite the massive upside of Facial Recognition Payments, the current adoption rate of FRP is still relatively low compared to traditional payment methods such as cash, card, and other biometric payment authentication methods. When individuals consider whether to use and continue using a system or service, both positive factors, known as enablers and negative factors, known as inhibitors, are considered (Cenfetelli, 2004). Where systems expose financial and privacy security concerns, individuals become increasingly reluctant to utilise such a service or system (Oliveira et al., 2016; N. Singh et al., 2020). Given that FRP is still relatively new as a payment system, there is a significant lack of research on how users view FRP as a payment choice (N. Singh et al., 2020). Most of the prior research has focused on payment through mobile applications, biometric credit cards and other more traditional payment methods (Dijmărescu et al., 2022; Kumar & Ryu, 2009; J. Li et al., 2014; Okumus & Bilgihan, 2014).

Zhang & Kang (2019) utilised the technology acceptance model (TAM) along with the unified theory of acceptance and use of technology (UTAUT) model to analyse factors that may affect the intention to utilise FRPS for users in China. The results indicated that consumers' perceived security, social image, visibility and expected judgments directly impact users' intention to facilitate an FRPS, while perceived efficacy seems to mediate the correlation between expected judgements and the intention to use FRPS.

2.3. A Review of Theoretical Applications

2.3.1. Innovation Resistance Theory (IRT)

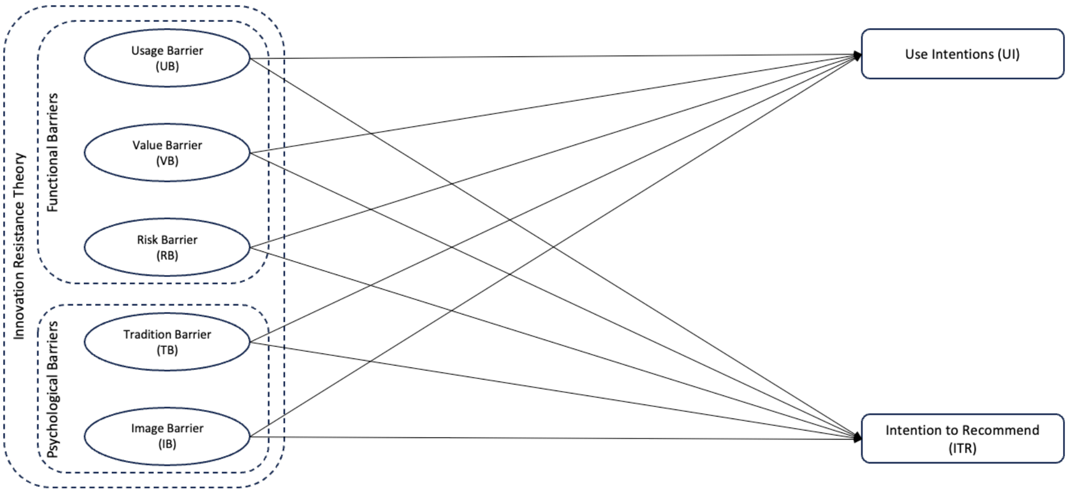

Figure 1. Innovation Resistance Theory

Source: Adapted from Ram & Sheth (1989)

Innovation Resistance Theory (IRT) presents a theoretical framework for user resistance and further aids in the comprehension of the resource-oriented behaviour of users (Ram & Sheth, 1989). Innovation resistance could be described as behaviour emanating from logical reasoning and the subsequent decision-making process regarding adopting and using innovation due to potential changes introduced to the current situation and deviations from a prevailing belief system (Hew et al., 2019). Consumer resistance could thus significantly impact the realisation of success or lead to the absolute failure of innovations (Ram & Sheth, 1989). Changes in users' lives, circumstances, and behaviour due to innovation can prompt resistance-oriented behaviour in these users (Ram & Sheth, 1989).

User resistance to innovation could also be viewed as “active and passive resistance” behaviour (Heidenreich & Handrich, 2015). Active resistance is viewed

as a resistive behaviour that emanates via the characteristics or features of innovations and can be analysed through functional barriers proposed by the IRT framework (Yu & Chantatub, 2015). These resistance factors represent the impediments relating to innovation adoption and subsequent usage resulting from the conflicts caused due to the behavioural contradictions arising from the innovation's use, value, and risk (Yu & Chantatub, 2015). Passive resistance results from conflicts within an existing belief system and can be analysed through the psychological barrier lens provided by the IRT framework (Yu & Chantatub, 2015).
The comprehensive nature of the IRT framework makes it suitable for examining the inhibitors of users' resistance towards innovations (Ma & Lee, 2019). IRT's focus on explaining users' response to innovation regarding the identified barriers (usage, value, image, risk, and tradition) provides the research with a sound theoretical foundation for understanding and explaining innovation resistance behaviours. This understanding becomes critical as innovation continues to occur across a wide array of markets.

IRT has been utilised as the primary theoretical framework to investigate the barriers and user resistance towards various technology innovations that impact the user and their intent to utilise such innovation. Such examples include Online shopping and e-commerce (Soh et al., 2020), mobile banking services (A. S. Yang, 2009), mobile commerce applications (Moorthy et al., 2017), and mobile payment services (Migliore et al., 2022).

2.3.2. The Technology Acceptance Model

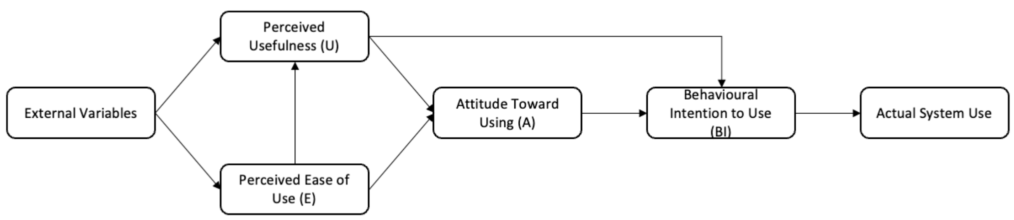

Figure 2. The Technology Acceptance Model

Source: Adapted from (Davis, 1986)

The Technology Acceptance Model (TAM) is a framework that assesses a user's acceptance and adoption of new technologies. Introduced by Davis (1989), TAM has become a foundation for assessing users' willingness to adopt and use a new technology.

The TAM utilises external variables to assess Perceived Ease of Use (E), Perceived Usefulness (U) and how the consumers' Behavioural Intention to Use (BI) is then affected and how these culminate in Actual System Use (AU).

This model has been utilised to assess consumers' BI and AU across various technology acceptance spheres, including consumers' BI in FRPS (W. K. Zhang & Kang, 2019).

2.3.3. Unified Theory of Acceptance and Use of Technology

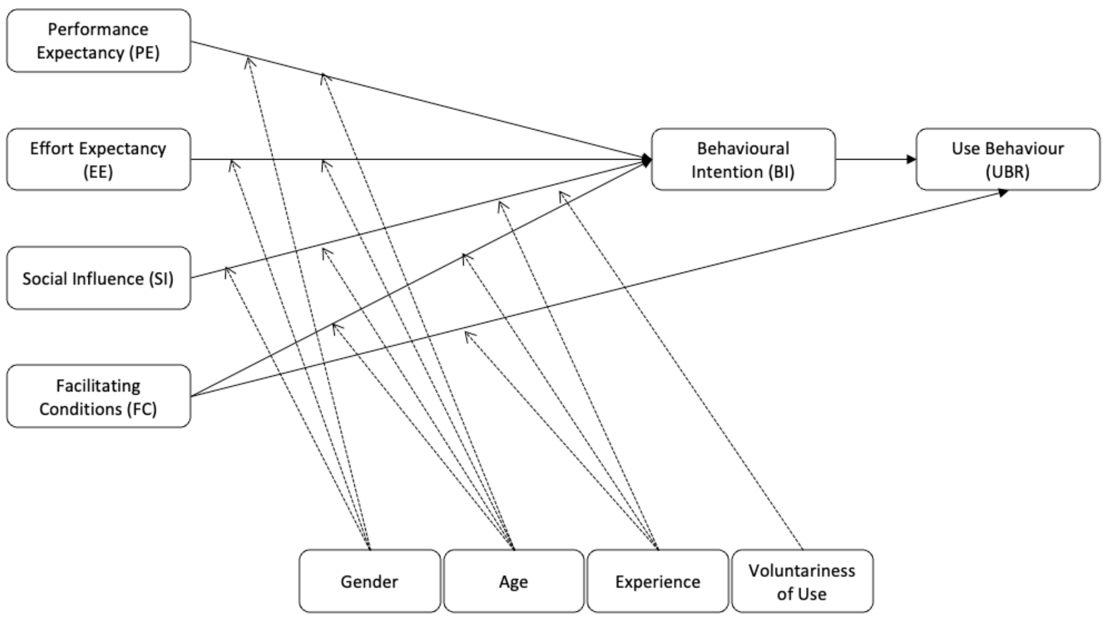

Figure 3. The Unified Theory of Acceptance and Use of Technology Model

Source: (Venkatesh et al., 2003)

The Unified Theory of Acceptance and Use of Technology (UTAUT) framework has been long developed and utilised to understand and predict users' acceptance, adoption, and usage of technology (Venkatesh et al., 2003).

The model has been a primary tool used in various biometric and FRPS studies in recent times to understand and predict users' adoption of FRPS. W. K. Zhang & Kang

(2019) used UTAUT to research consumers' intent to use FRPS, which used security, visibility, expected effort and social image to explore perceived usefulness and, subsequently, the intent to use. W. K. Zhang & Kang, (2019) found that the independent variables within the model all significantly affected the dependent variable (BI).

2.3.4. Technology Adoption Decision Model

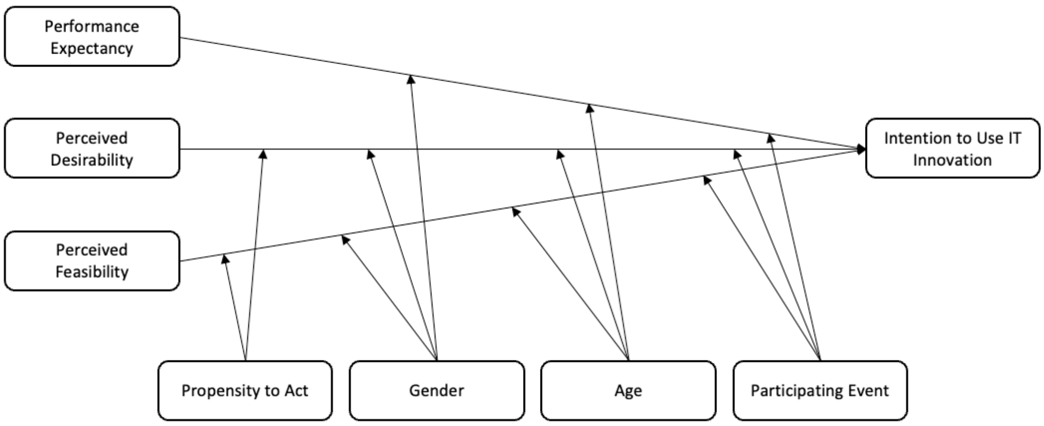

Figure 4. Technology Adoption Decision Model

Source: (Moghavvemi et al., 2017)

The Technology Adoption Decision & Usage (TADU) framework, as illustrated by Moghavvemi et al. (2017) was constructed to test the intentions of entrepreneurs to adopt and utilise technological innovation within their business environments. The model tests the impact of Performance Expectancy (PE), Perceived Desirability (PD) and Perceived Feasibility (PF) to understand the effect on the intention to use. This research found that the effect of PD on BI was significant.

2.3.5. Status Quo Bias

The concept of Status Quo Bias (SQB) states that user resistance can be attributed to the user's desire to remain with a current situation when faced with a decision (Samuelson & Zeckhauser, 1988).
Inertia in the context of decision-making stems from the theory of Status Quo Bias (SQB), which reasons that individuals will maintain an existing action or habit even

when presented with the choice of enabling or enacting a seemingly superior action (Samuelson & Zeckhauser, 1988). Defined as a conscious effort to stay with the status quo (Polites & Karahanna, 2012), inertia represents a resistance to change or a preference to stay with the status quo, which can significantly inhibit technology adoption.

In marketing and sales, inertia is used to predict a consumer's intention to continue engaging with a particular brand or service (Polites & Karahanna, 2012). Inertia is a significant variable for determining repeat consumer behaviour within the payment environment (Amoroso & Ogawa, 2013). Inertia is imperative in explaining consumer satisfaction with various applications and is essential for service providers who count on repeat usage to drive adoption and revenue. Inertia has significantly influenced users' intentions to accept or reject technology in prior research (Amoroso & Ogawa, 2013).

2.3.6. The role of moderation

Technology acceptance behaviour has received significant coverage, with numerous models and theories developed to explain user acceptance. These models are, however, not without limitation. The explanatory power of these models constitutes the first limitation, with many studies explaining less than 60% of variance through these devised models (Sun & Zhang, 2006). The second limitation noted among studies is the varying relationship between constructs, which draws concerns about how the results of one study could be applied to another given various models and contexts (Y. Lee et al., 2003). These limitations have long been requisite to introduce improvement and refinement of existing and future research (Sun & Zhang, 2006).

Moderating factors have been shown to account for the limited explanatory power and inconsistencies between various research conducted on technology acceptance (Adams et al., 1992; Sun & Zhang, 2006; Venkatesh et al., 2003). As a result, moderating factors were deemed necessary to improve the explanatory effect and the generalisability of this study.

2.3.7. Desirability as a Moderator

Moghavvemi et al., (2017) illustrated desirability as significantly impacting individuals' BI, utilising TADU as the primary framework. Consumers' desirability to drive BI was further tested, and it found higher levels of perceived desirability affected consumers' adoption (Kulviwat et al., 2009). Given that Desirability could influence consumers' decision to adopt or reject, it was deemed appropriate to consider Desirability as a Moderating factor within the study.

2.4. Examination of Constructs

2.4.1. IRT Barriers and the Use Intention

The proposed research model thus utilises the IRT framework to build out the hypotheses below.

Usage Barriers

Usage barriers speak to the interference instigated by probable changes involved in the process of adopting innovations when compared to the use of existing systems (Ram & Sheth, 1989). In this example, the usage barrier construct addresses the effort the user needs to learn and utilise the new FRPS system. Heidenreich & Handrich (2015) position that higher levels of deviation from existing practices result in higher adoption resistance.

Hypothesis relating to usage barriers;

H_1: Usage barriers are negatively correlated with the use intention towards FRPS.

Value Barriers

Value barriers refer to the resistance emanating from the inconsistencies found within the value system, particularly within the users' view when weighing the cost of learning and utilising the innovation against the benefits on offer (Morar, 2013). Ideally, the perceived benefits should outweigh the perceived cost to encourage and drive usage.

Proposed hypothesis relating to value barriers;

H_2: Value barriers are negatively correlated with the use intention towards FRPS.

Risk Barriers

Risk barriers refer to resistance which results from uncertainties arising from the utilisation of the innovation. It is suggested that acceptance of an innovation is influenced by the level of uncertainties introduced by the innovation in question (Dunphy & Herbig, 1995). It is generally accepted then, that innovation with lower levels of uncertainties leads to higher levels of innovation acceptance and adoption.

Proposed hypothesis relating to risk barriers;

H_3: Risk barriers are negatively correlated with the use intention towards FRPS.

Tradition Barriers

Tradition barriers relate to the challenges presented by innovation if the innovation in question introduces a change to a user's existing routine, behaviour, or culture (El Badrawy et al., 2012). It is contended that traditions are entrenched within society and in individuals' lives and that a possible conflict with traditions could result in resistance towards the innovation that introduces such conflict and a negative impact on innovation acceptance (John & Klein, 2003).

Proposed hypothesis relating to tradition barriers;

H_4: Tradition barriers are negatively correlated with the use intention towards FRPS.

Image Barriers

Image barriers refer to the aspect of negative impressions associated with the innovation which stems from the apparent levels of complexity that is associated with the use of the innovation (Lian & Yen, 2013). As an example, there are several privacy concerns associated with the use of FRPS (Liu et al., 2021), which contributes towards building a negative image in terms of the adoption and usage of the FRPS innovation.

Proposed hypothesis relating to image barriers;

H_5: Image barriers are negatively correlated with the use intention towards FRPS.

2.4.2. TAM Inhibitors, Use Intention, and the Intention to Recommend

After the core design of the research model for this study, an application of alternative, independent variables were introduced to further test users' inhibition to adopt and to recommend FRPS. As part of the research methodology, external factors are introduced in the TAM model to measure potential inhibitors to the adoption of FRPS. These factors are notably, Inertia and Mistrust as the independent variables which are analysed for their impact on Use Intention and Intention to Recommend.

Inertia

Within the context of technology adoption, Inertia refers to the resistance of entities to change their existing technology-related behaviour. In the context of FRPS, inertia refers to the individuals' resistance to switching from an existing, known payment method to FRPS.

Inertia has been shown to significantly affect a user's propensity to adopt new payment technology with users displaying greater levels of Inertia, likely to be satisfied with, and remain with existing technology (Samuelson & Zeckhauser, 1988), even if there are better alternatives to use, thus these users will display higher levels of resistance to adoption to FRPS.

Proposed hypothesis relating to Inertia;

H_6: Inertia is negatively correlated with the use intention towards FRPS.

H_7: Inertia is negatively correlated with the intention to recommend FRPS.

Mistrust

Mistrust can hinder technology adoption by creating barriers and reluctance among individuals, businesses, and organisations. Where discomfort arises from acuities of lack of control over technology and feeling overwhelmed by it, insecurity involves distrust of technology and scepticism about its ability to work correctly (Parasuraman, 2000). Technical readiness further determines how prepared and proficient a user is to adopt an innovation (Iacovou et al., 1995; Kuan & Chau, 2001), but the technical challenges that lie within the systems may call on the user to possess both technical skills as well as sufficient knowledge about the innovation. If these are insufficient, users may feel vulnerable to potential exploitation (Mysen et al., 2011), which amplifies the element of potential risk and in turn, affects the users' adoption and use of the technology (Pavlou, 2002; Pressey & Ashton, 2009).

Where mistrust is prevalent, people are more likely to reduce their adoption rate of new technologies as they adopt a waiting position, ultimately delaying their adoption until they are more confident and trusting in the technology (Sandada et al., 2016).

Proposed hypothesis relating to Mistrust;

H_8: Mistrust is negatively correlated with the use intention towards FRPS.

H_9: Mistrust is negatively correlated with the intention to recommend FRPS.

2.4.3. Moderation of TAM Inhibitors

Desirability

Moghavvemi et al., (2017) illustrated desirability as significantly impacting individuals' BI, utilising TADU as the primary framework. Consumers' desirability to drive BI was further tested, and it found higher levels of perceived desirability affected consumers' adoption (Kulviwat et al., 2009). The link between BI and UI could result in UI being influenced the perceived desirability of FRPS, hence the four hypotheses to test the moderation of DI;

H_{10}: Tradition barriers are negatively correlated with the use intention towards FRPS.

H_{11}: Tradition barriers are negatively correlated with the use intention towards FRPS.

H_{12}: Tradition barriers are negatively correlated with the use intention towards FRPS.

H_{13}: Tradition barriers are negatively correlated with the use intention towards FRPS.

2.5. Conclusion

Chapter 2 presented a review of existing literature which had focused on technology adoption, and resistance towards the use and adoption of FRPS. The chapter further dissected potentially appropriate theoretical frameworks that could be considered for the study and subsequently formulated a set of hypotheses which aim to address the research question introduced in Chapter 1.

A total of 13 hypotheses were formulated, which aim to explore Use Intention and Intention to Recommend and test the moderation impact of Desirability of the Independent Variables of Inertia and Mistrust.

3. Chapter Three: Conceptual Model, Research Questions and Hypotheses

3.1. Introduction

The conceptual model that was developed and proposed for this study emanates from the study and review of existing literature presented in Chapter 2, where the IRT barriers form the basis for formulating the hypotheses in facial recognition payments. Chapter 3 introduces the conceptual model that was developed and elaborates on the hypotheses that were formulated.

3.2. Conceptual Model

Figure 5 below graphically illustrates the conceptual model formulated for this study. The model, founded on the analysis of IRT barriers against UI incorporates elements of Inertia, Mistrust and moderated by Desirability. These variables that were reviewed during the examination of TAM, TADU and UTAUT and are deemed to be appropriate to expand the model in attempt to gain the relevant insights required to respond to the research question.

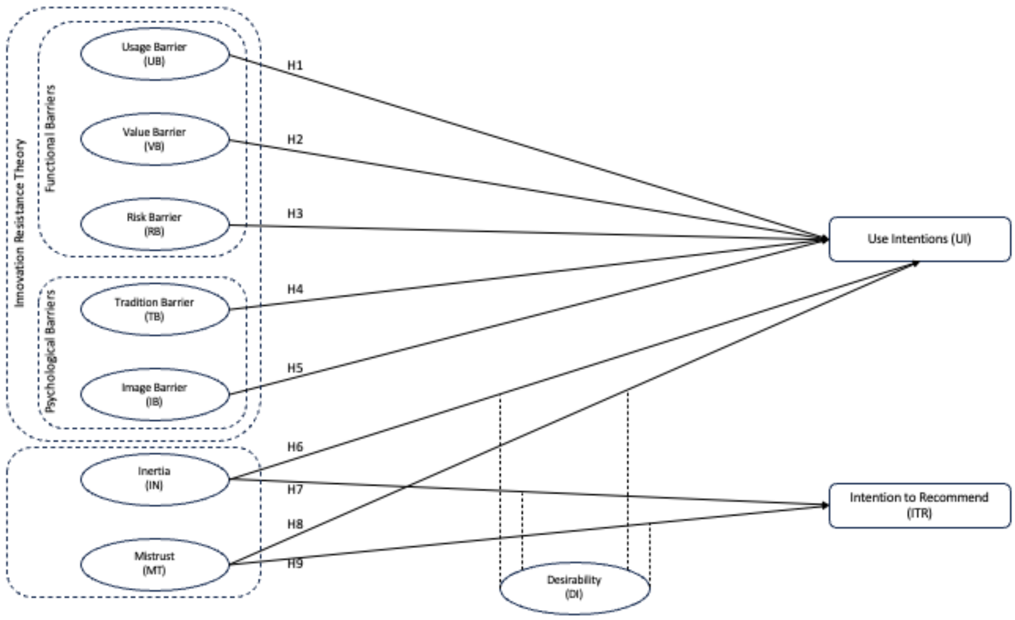

Figure 5. Research Model

3.3. Research Model & Hypotheses

The Innovation Resistance Theory framework was deemed as the appropriate framework to be utilised to devise a research model for the measurement of the way preadoption barriers tend to influence the behaviours of Facial Recognition Payment Systems (FRPS) users in terms of their intention to use and to continue to use and their intention to recommend the system to other users. The devised model is represented in Fig. 5.

The independent variables proposed for use are the five IRT barriers: value, image, risk, usage and traditional. The two proposed dependent variables to be used are (1) Use Intentions (UI) and (2) the users' Intentions to Recommend (IRT). These proposed dependent variables represented frequently utilised postadoption indicators that measured the intent of users to continue with the use of a product and their intent to raise positive word-of-mouth indices, which can be viewed as a persuasive aspect in the adoption-related decision-making process (Moldovan & Goldenberg, 2004). Prior research on technology adoption indicated that the results of negative word-of-mouth can be devastating as the negative connotations derived from this action can have a brutally negative impact on service providers by delaying or even perpetually obstructing the transmission process (Gurtner, 2014). Moldovan

& Goldenberg (2004), noted in their work that consumers are inclined to participate in negative word-of-mouth activities when actively opposed to a change or when they are not satisfied with a product or service.

Whilst prior literature has examined the association between the functional and the psychological barriers and the users' ITR for first-time mobile payment solutions (MPS) (Kaur et al., 2020), there is a distinct lack of research applied within the realm of FRPS.

H_1: *Usage barriers are negatively correlated with the use intention towards FRPS.*
H_2: *Value barriers are negatively correlated with the use intention towards FRPS.*
H_3: *Risk barriers are negatively correlated with the use intention towards FRPS.*
H_4: *Tradition barriers are negatively correlated with the use intention towards FRPS.*
H_5: *Image barriers are negatively correlated with the use intention towards FRPS.*
H_6: *Inertia is negatively correlated with the use intention towards FRPS.*
H_7: *Inertia is negatively correlated with the intention to recommend FRPS.*
H_8: *Mistrust is negatively correlated with the use intention towards FRPS.*
H_9: *Mistrust is negatively correlated with the intention to recommend FRPS.*
H_{10}: *Desirability has a moderating effect on Inertia and the use intentions of FRPS.*
H_{11}: *Desirability has a moderating effect on Inertia and the Intention to Recommend FRPS.*
H_{12}: *Desirability has a moderating effect on Mistrust and the use intentions of FRPS.*
H_{13}: *Desirability has a moderating effect on Mistrust and the Intention to Recommend FRPS.*

3.4. Conclusion

The conceptualised model incorporates IRT as the primary framework underpinning this study. Including external variables (Inertia and Mistrust) was deemed appropriate to broaden the scope of the IRT framework to address the research question raised in the first chapter. Furthermore, the impact of Desirability as a moderator aims to explain the relationship between the Independent and Dependent variables included in the model.

4. Chapter Four: Research Methodology

4.1. Introduction

This chapter details the research methodology employed for this study, devised following the construction of the hypotheses introduced in Chapter 2, and the conceptual model details in Chapter 3. The methodology was derived from the review of existing literature and theory and applied accordingly. The chapter describes the research design choice and then elaborates on the intended target population, the selected sampling method, and the subsequent data-gathering process. The chapter details the data processing and analysis techniques employed to run quality measurements against the data. The statistical methodology used to test the proposed hypotheses is then described. The chapter closes with the limitations of the chosen research methodology.

An explanatory research design was employed to explain why consumers would potentially shy away from adopting facial recognition as a primary or frequent payment method.

4.2. Choice of Research Design

The research design was crafted to provide clarity pertaining to the research problem stated in Chapter 1. The design was intended to demonstrate the potential inhibition of individuals when using or recommending FRPS, through the study utilising a deductive approach (Saunders & Lewis, 2018).

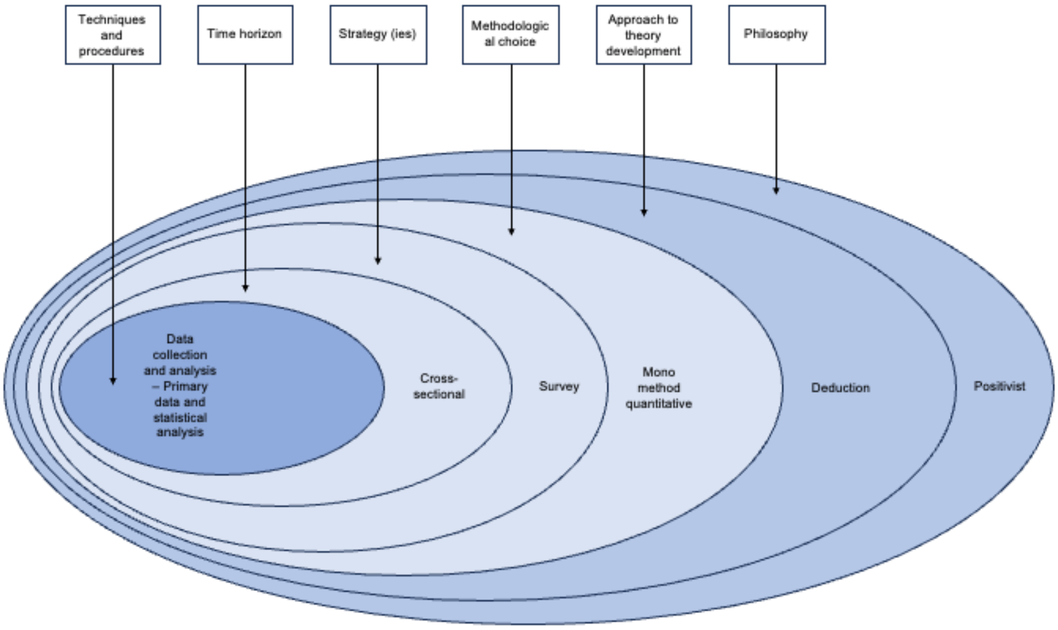

Figure 6. Research design illustrated using the research onion.

Source: Adapted from Saunders & Lewis (2018)

4.2.1. Philosophy

The research study adopted a positive approach, providing a rigorous and systematic framework for studying the relationships in question. This approach was based on the research methodology that ideates that the social world can be studied using objective and measurable methods to discover and explore potential relationships, patterns or laws that could be applied in context (Bryman, 2016).

In this case of facial recognition payments, the positivist approach allowed the identification and testing of hypotheses relating to the factors that influenced the use of facial biometrics as a payment option. The positivist approach further allowed a solid empirical basis for evaluating the potential benefits and risks of utilising facial recognition payments and comparing them directly against other payment methods such as cash and cards. Through adopting a positivist philosophy, the author collected and analysed a significant volume of quantitative data and utilised statistical inference to derive meaningful insights and conclusions concerning the hypotheses (Alharahsheh & Pius, 2020). The positivist approach offered a robust and objective means of unpacking facial recognition payment data, which aided in informing the design and implementation of this payment method by interested parties.

4.2.2. Approach to Theory Development

A deductive approach to theory development was utilised, which involved developing a set of theories and hypotheses and testing these through empirical observation and data collection (Gallaire et al., 1984). In the context of this study, the approach involved beginning with a theoretical framework about the general resistance to innovation adoption and was subsequently applied to the realm of facial recognition payments. The study analysed potential inhibitors associated with using facial biometric payment systems. The formulated hypotheses thus illustrated a set of inter-related characteristics pertaining to the perception of facial recognition payments and the user's propensity to use the payment method.

4.2.3. Methodology

The study adopted a mono-methodological design framework, enabling data collection through a single technique (Saunders & Lewis, 2018). This approach allowed the author to focus on the collection and analysis of numeric data quickly and efficiently, given the time constraints of the study and was thus deemed appropriate for the study.

4.2.4. Research Strategy

The study utilised a survey as the primary data collection source. The survey approach to the study aimed to analyse to what extent the impact that social anxiety has on consumers and their subsequent inclination to adopt and use facial recognition payment systems. A survey-based approach fundamentally aided the study in understanding the relationship between the identified variables (Sukamolson, 2007).

4.2.5. Time Horizon

The data utilised for the study was collected at a specific point in time. The research was thus deemed to be cross-sectional in nature and sought to collect data through self-completed and interviewer-completed questionnaires (Saunders & Lewis, 2018). This was deemed appropriate given the timelines and project deadlines.

The deductive approach provided a systematic and structured way to test the formulated hypotheses and evaluate the validity of theoretical frameworks, making it a viable methodology theory for studying FRPS (Bloomfield & Fisher, 2019).

4.3. Population

The study aimed to investigate relationships between factors contributing to the resistance to adopting and using facial recognition payment systems. To achieve this, the target population of users would be open to any adult over the age of 18 as this population is deemed to be in scope to utilise facial recognition frequently under most regulatory boards (Walters et al., 2019). The survey was distributed directly to residents within South Africa and posted on various social media platforms. The study was non-restrictive in demographics as it aimed to broadly understand potential inhibitors for adopting FRPS as a payment method of choice, irrespective of consumers' existing payment preferences.

4.4. Unit of Analysis

The purpose of the study was to analyse and better understand the potential inhibitors regarding the use of technology innovation under IRT pertaining to FRPS. The conceptual model was designed to explore the effect of the barriers within IRT on users' inhibition to utilise facial recognition payment systems. Thus, the study utilised the individual's inhibition to utilise technology as the unit of analysis. Utilising an individual's inhibition as the unit of analysis illustrates that the intent of the study is focused on understanding the traits of an individual; their characteristics, experiences, behaviours, and attitudes could potentially affect the individual's propensity to utilise facial recognition payments (Ram & Sheth, 1989).

Additionally, the study unpacks the moderating effects of Desirability on Inertia and Mistrust in the adoption or rejection of technology.
The study aimed to uncover users' propensity to utilise or discard the use of facial recognition payments based on various factors, including technological anxiety and privacy factors, and questions to the respondents will be aligned to these focus areas.

4.5. Sampling Methods

The proposed sample size and characteristics of the sample relative to the study should be suitably associated with the research problem and, subsequently, aligned with the research questions to aid an optimal outcome (Köhler et al., 2017). It is further positioned that for inferential statistics to effectively utilise quantitative methodologies, the selected sample should represent the population appropriately (Zyphur & Pierides, 2017).
The author aimed to target shoppers utilising formal retail environments across various spheres, irrespective of whether they had previously utilised digital or biometric payment methodologies to transact.
The nature of probability sampling methods aids in obtaining a representative sample for the study. As the author aims to understand a user's behaviour based on social anxiety, a representative sample is required to ensure non-biased results and will aid in a higher level of confidence when drawing inferences to the population as a whole (Goodman & Kish, 1950), however, practically, probability sampling was not feasible given the time constraints of the study and the vast population that was deemed to be in scope thus a non-probability sampling method was instituted (Saunders & Lewis, 2018).

The survey was distributed to the researcher's contacts, who were the initial respondents. The respondents were then requested to distribute the survey to their network to achieve the minimum viable response rate. In terms of the non-probability sampling methodology employed, it is noted that a snowball sampling method was utilised to increase the accessible audience and improve the probability of gaining sufficient individual responses to deem the data collection complete (Saunders & Lewis, 2018). The final sampling method was consequently noted as a non-probability snowball sampling method.

4.6. Sampling Size

The number of samples collected is equally critical as that of the sampling method. Köhler et al. (2017) state that if the quantity of responses collected within a dataset is insufficient, the outcome of the statistical analysis will be likely to not yield results that could appropriately inform the requisite insights, deeming the results unreliable. The sample size was further explored by (Hair, 2009) and (Delice, 2010), who note that the achieved sample size significantly affects the outcome and ambition to achieve meaningful results. It was proposed that a minimum of 100 responses is required for hypothesis testing (Cleff, 2019; Hair, 2009).

To improve the sample generalisability and ensure a sufficient sampling size by increasing the degrees of freedom (Cleff, 2019; Hair, 2009), an A-priori sample size calculator was utilised for Structural Equation modelling to achieve a more accurate sample size (Soper, 2023). Using the number of latent and observed variables evident in the model illustrated in (INSERT FIGURE), a minimum of 138 questionnaires was noted as the minimum viable sample size required. This minimum sample size was used to account for failures in quality measures or incompleteness and ensure a sufficient sample size could be used to draw significant representation from the target population (Delice, 2010).

4.7. Measurement Instrument & Data Gathering Process

Primary data gathering was performed by developing and distributing a structured questionnaire. The questionnaire was developed with closed-ended responses, as illustrated in Appendix A. The questionnaire used for the research was adapted from previous studies that have utilised similar approaches using IRT and TAM in the field of facial recognition payment technology and analysed consumers' propensity to use or not use facial recognition as a payment instrument. The questionnaire included factors that focused on barriers affecting users’ affinity to utilise mobile payment technology, biometric familiarity, and other relevant factors. The survey was structured such that all respondents were subject to matching flows, meaning that the respondents answered the same questions in the same order (Saunders & Lewis, 2018).

The cover letter included both the informed consent and context into the intent of the survey based on trends identified as part of the literature review of the research. Allowance was made for simple demographic information, followed by the various constructs in the proposed conceptual model. All questions were designed to be mandatory, which reduced the likelihood of incomplete responses.

The survey consisted of eleven short sections which are detailed in Appendix A. The sections were determined as follows:

Section 1: Comprised of the informed consent and cover page.
Section 2: Consisted of demographic information (Chronological Age, Education Levels, Gender and Employment Status).
Section 3: Consisted of questions relating to Desirability which was required to gain insight into potential moderation impact of DI.
Section 4: Consisted of two questions relating to potential inhibition introduced by Value Barriers.
Section 5: Consisted of four questions relating to potential inhibition introduced by Tradition Barriers.
Section 6: Consisted of three questions relating to potential inhibition introduced by Image Barriers.
Section 7: Consisted of five questions relating to potential inhibition introduced by Risk Barriers.
Section 8: Consisted of four questions relating to potential inhibition introduced by Usage Barriers.
Section 9: Consisted of five questions relating to Use Intention and Intention to Recommend.
Section 10: Consisted of four questions relating to general views of Inertia.
Section 11: Consisted of four questions relating to views of Mistrust within FRPS.

The data collected from the survey was deemed to be both nominal and interval data, with section two consisting of nominal data (demographic information) and sections three through eleven consisting of interval data derived from existing theory. A five-point Likert scale was employed for the responses within sections three through eleven, with one allocated to “strongly agree” and five allocated to “strongly disagree”. The decision to utilise the five-point Likert scale over a higher interval scale, was selected to limit the potential deviation in results and was selected based on the review of existing literature within IRT and TAM in Chapter 2.

A pilot study was completed to test and critique the questionnaire before continuing with the full-scale distribution to respondents for final data collection. The pilot was utilised to test and ensure the questions in the survey were unambiguous to the targeted audience. The pilot further allowed the testing of the online data collection tool to ensure that no errors or deviations in answers were received. Verbal feedback was received from the pilot respondents, and the questionnaire was deemed appropriate and clear. The online tool was deemed fit for purpose as all recorded answers were recorded without error. The pilot responses were excluded from the primary data collection process.

4.8. Data Gathering Process

Data for the study was gathered via the completion of an online survey. The surveys were hosted on the Google Forms online platform, web-based, and self-administered by the respondents. The initial survey respondents were accessed via engagement with the researchers' contacts, colleagues, and social networks. The targeted respondents were initially sent a direct message via email, WhatsApp, text, or social media platforms such as LinkedIn and Facebook. Following this initial engagement, a link to the survey was posted across the researcher's various social media platforms, and respondents were encouraged to voluntarily complete and share the survey and the link with their networks. As a result of this approach, a snowball sampling technique was then deemed to have been utilised as the primary distribution methodology post the initial distribution of the survey to the researchers’ direct contacts (Saunders & Lewis, 2018).

Conditional ethical clearance was received on the 4th of September 2023 and required minor amendments in terms of data storage. Final ethical clearance for data gathering was granted on the 11th of September 2023 (see Appendix B), whereafter the pilot study was conducted. The pilot was completed during the following five days, and the questionnaire was analysed for shortcomings. The questionnaire was found to be fit for purpose, and the formal data collection commenced and ran for approximately two weeks from mid-September 2023 to end-September 2023. These questionnaires were both self-completed and interviewer-assisted surveys and were collected via an omnichannel approach, including digital channels and in-person surveys. The participants entered the entries directly into the Google Forms questionnaire.

The data was stored on a password-protected cloud storage device, synchronising daily with the researcher's physical, password-protected hard drives. The researcher has further uploaded the data onto the research institution's formal records and will maintain the data for an absolute minimum of ten years following the submission of the study.

4.9. Data Preparation & Coding of Data

Following the closure of the survey window, the collected responses were downloaded and imported into Microsoft Excel. The online survey was designed to mandate the completion of each question; however, before analysis commenced, the dataset was cleaned and checked to ensure all surveys were complete and no errors were evident in the responses. The responses were found to be free of errors and the respondents fully completed all 303 received surveys.

Once the data had been successfully imported into Microsoft Excel, the data was coded in preparation for the final data analysis. Each survey question was assigned a unique identification label and numeric codes were assigned to the nominal (demographic) data. Each variable was aligned to the five-point Likert scale with 1 assigned to “Strongly Agree” and 5 to “Strongly Disagree”.

4.10. Analysis Approach

Partial Least Squares Structural Equation Modelling (PLS-SEM) was deemed the appropriate data analysis technique. The suitability of PLS-SEM was assessed based on the recommended sample size and the consistency of the assumptions for using a multivariate analytical approach. PLS-SEM will allow the research to assess latent constructs' measurement properties and their structural relationships.

Descriptive statistics were analysed broadly to illustrate the data's basic features. Analytical observations include the demographic data's mean, mode, median, range, and standard deviation. These measures aid us in understanding of the central tendency, dispersion, and the overall shape of the data (Goertzen, 2017).

Correlation analysis was used to determine the strength and direction of the relationship between two or more variables. It will aid us in understanding the degree to which two variables are related to each other (Goertzen, 2017).

Factor analysis was used to identify patterns in the data and to group variables into factors that are related to each other. Factor analysis aids in exploring underlying factors that explain the observed patterns in the data (Goertzen, 2017).

4.11. Quality Controls

The surveys were designed to ensure completeness by mandating all questions to be completed within the survey. Additionally, two attention checks were embedded into the questionnaire to identify inattentive respondents who may not have completed the questionnaire attentively (Oppenheimer et al., 2009).

4.12. Descriptive Statistics

Descriptive statistics was used to broadly understand the data collected from a demographic perspective. Whilst the demographic information collected was considered insignificant in this study, the information analysed will assist in identifying potential limitations or gaps within the dataset.

4.13. Pre-Testing of Constructs and Measurement Instrument

Pre-testing of constructs and measurement of the instrument were performed to test the validity and reliability of the model. Pearson’s product-moment correlation analysis was performed to investigate the relationship between the variables. Discriminant and convergent validity analyses were performed under the measurement model.

4.13.1. Validity & Reliability

Verifying construct validity and reliability is a crucial step during the evaluation process (Hair Jr et al., 2014).
Reliability tests were performed to evaluate and assess the correlation of relationships between all items within the construct. A Pearson Product-Moment correlation analysis was performed to measure the strength and direction of the relationships between the variables (Puth et al., 2014). The strength of the relationship Pearson correlation coefficient provides a numerical value between -1 and 1, where we note -1 denotes a perfect negative relationship, 1 denotes a perfect positive relationship, and 0 indicates no linear relationship exists.

4.14. Hypothesis Testing

#	Hypothesis	Hypothesis Type
H_1	*Usage barriers are negatively correlated with the use intention towards FRPS.*	Relationship
H_2	*Value barriers are negatively correlated with the use intention towards FRPS.*	Relationship
H_3	*Risk barriers are negatively correlated with the use intention towards FRPS.*	Relationship
H_4	*Tradition barriers are negatively correlated with the use intention towards FRPS.*	Relationship
H_5	*Image barriers are negatively correlated with the use intention towards FRPS.*	Relationship
H_6	*Inertia is negatively correlated with the use intention towards FRPS*	Relationship
H_7	*Inertia is negatively correlated with the intention to recommend FRPS.*	Relationship
H_8	*Mistrust is negatively correlated with the use intention towards FRPS.*	Relationship
H_9	*Mistrust is negatively correlated with the intention to recommend FRPS.*	Relationship

H_{10}	*Desirability has a moderating effect on Inertia and the use intentions of FRPS.*	Moderated
H_{11}	*Desirability has a moderating effect on Inertia and the Intention to Recommend FRPS.*	Moderated
H_{12}	*Desirability has a moderating effect on Mistrust and the use intentions of FRPS.*	Moderated
H_{13}	*Desirability has a moderating effect on Mistrust and the Intention to Recommend FRPS.*	Moderated

Table 2. Generated Hypotheses and Type

4.15. Limitations

Given the nature of the general research process, Saunders & Lewis (2018) note that research studies are naturally prone to limitations. The following limitations were identified for this study.

The data that was collected may have been concentrated within groups of individuals sharing common traits due the use of snowball sampling methodologies. This could have resulted in a degree of similarity within the analysed data set and resulted in a sampling bias.

The cross-sectional timeline of the study limited results that emanated from the formulated hypotheses and associated statistical analyses. Conducting the study within a limited time frame is seen to have impacted the depth of the analysis and hindered the ability to drive a comprehensive probability sampling methodology.

While the focus of the study has primarily been on inhibitors influenced by IRT barriers and external factors under TAM, there are further considerations that can affect the inhibition of users' intention to adopt the technology.
The impact of resistance is significantly influenced by the age of the adopter, with mature consumers showing higher levels of resistance to change than their younger counterparts.

4.16. Conclusion

This chapter details the approach that was adopted for this study. The research design was explained and supported through the examination of previous studies and subject matter experts.

The study design, data collection methodology and sample population were deemed to be appropriate for the study and it was noted that a sample pilot study was conducted prior to the primary data gathering process. The pre-validation of the data and subsequent model tests were described which were then carried out and detailed in the fifth chapter.

5. Chapter Five: Research Findings and Results

5.1. Introduction

The following section contains the results of the analyses performed on the collected data *(N=303)*. A total of 13 hypotheses were formulated in and were subsequently tested, the results of which are detailed in this chapter. The chapter consists of hypothesis testing and structural equation modelling using Smart-PLS. The initial section details the results of Pearson’s product-moment correlation analysis. Pearson’s product-moment correlation analysis was performed to investigate the relationship between the variables; the results are presented in *Table 3*. In the second section, the reflective constructs were measured in *Table 4*, and discriminant and convergent validity analyses were performed under the measurement model *(Tables 5 and 6)*. Finally, a structural model analysis was conducted, and the path analysis and moderation analysis were carried out as modelled in *Figure 7*.

5.2. Correlation Analysis

Pearson's product-moment correlation analysis was performed to evaluate and measure the linear relationship between variables contained in the model (Puth et al., 2014), and the analysis results are presented in Table 3 below.

	M	*SD*	1	2	3	4	5	6	7	8	9	10
1.DI	9.73	4.33	-	-.71***	-.32***	-.66***	-.44***	-.67***	.80***	.78***	-.27***	-.52***
2.VB	6.79	2.09		-	.43***	.60***	.43***	.60***	-.67***	-.63***	.30***	.50***
3.TB	12.75	2.63			-	.43***	.24***	.34***	-.35***	-.30***	.35***	.33***
4.IB	10.86	2.61				-	.50***	.68***	-.70***	-.63***	.41***	.51***
5.RB	12.37	4.46					-	.43***	-.51***	-.44***	.18***	.63***
6.UB	12.89	3.66						-	-.71***	-.67***	.31***	.51***
7.UI	8.31	3.60							-	.86***	-.34***	-.58***
8.ITR	4.96	2.09								-	-.32***	-.56***
9.IN	15.17	2.58									-	.31***
10.MT	13.24	3.18										-

Note. **p*<.05, ****p*<.01, *****p*<.001, DI= Desirability, VB= Value Barrier, TB= Tradition Barrier, IB= Image Barrier, RB= Risk Barrier, UB= Usage Barrier, UI= Use Intention, ITR= Intention to Recommend, IN= Inertia, MT= Mistrust.

Table 3. Pearson product-moment correlation analysis of variables

Pearson's product-moment correlation analysis was carried out, and the results of the analysis showed that Desirability was found to be significantly negatively correlated with Value Barrier, Tradition Barrier, Image Barrier, Risk Barrier, Usage Barrier, Use Intention, Intention to Recommend, Inertia and Mistrust. Moreover, Value Barrier was also significantly but positively correlated with Tradition Barrier, Image Barrier, Risk Barrier, Usage Barrier, Inertia and Mistrust. However, it significantly negatively correlated with Use Intention and Intention to Recommend; further, the results revealed that Tradition Barrier was significantly positively correlated with Image Barrier, Risk Barrier, Usage Barrier, Inertia and Mistrust. They were found to have a significant negative correlation with Use Intention and Intention to recommend. Furthermore, Image Barrier was significantly positively correlated with Risk Barrier, Usage Barrier, Inertia and Mistrust. However, the Image Barrier was significantly negatively correlated with the Use Intention and Intention to recommend. Further, the results revealed that Risk Barrier was significantly positively correlated with Usage Barrier, Inertia and Mistrust. In contrast, a negative correlation was found between Risk Barrier, Use Intention, and Intention to recommend. Usage Barrier was further found to have a significant positive correlation with Inertia and Mistrust; however, a negative correlation with Use Intention and Intention to recommend. Moreover, Use Intention was found to have a significant positive correlation with Intention to Recommend, whereas a negative and significant correlation with Inertia and Mistrust. Furthermore, Intention to Recommend had a significant negative correlation with Inertia and Mistrust. Lastly, Inertia was found to be significantly positively correlated with Mistrust.

5.3. Structural Equation Modelling

Structural equation modelling (SEM) was performed utilising Smart-PLS. Given that the research model required path and moderation analysis, Smart-PLS was deemed a suitable statistical package for the analysis (Garson, 2013).
The Smart-PLS software package does not place reliance on the traditional fit indices (TFI) to achieve relevant model fit statistics. Henseler & Sarstedt, (2013) stated that Smart-PLS does not contain any presumptions of TFI. Compared to the Covariance-Based Structural Equation Model (CB-SEM), Partial Least Square Structural Equation Modelling (PLS-SEM) works on a single-item construct known as a formative indicator and a minimum 3-item construct as a reflective measurement. PLS-SEM does not require the samples or responses be significant in size. PLS-SEM has been shown to work on studies with as few as 10 responses (Peng & Lai, 2012). Two validities were assessed for reflective measures: convergent and discriminant validities. Composite reliability, Internal consistency, and AVE as the convergent validity. Heterotrait–Monotrait (HTMT) and Fornell–Larcker criteria were used for discriminant validity.

5.4. Assessment of the Measurement Model

The measurement model was assessed to measure the composite variables of the study (Hoyle, 1995). The assessment comprised convergent and discriminant validity analyses (Hoyle, 1995). For the internal consistency of the tool used in the study, a composite reliability test was performed, and Cronbach's Alpha was measured (Dijkstra & Henseler, 2015; Sarstedt et al., 2021). The convergent validity, the average variance extracted (AVE) of the construct and their factor loadings were measured as during the assessment of the proposed measurement model (Hair Jr et al., 2014) and the results are presented in Table 4 below.

Constructs	Items	Loading range	α	CR	AVE
Desirability	4	0.89-0.94	0.94	0.96	0.85
Value Barrier	2	0.89-0.92	0.79	0.91	0.83
Tradition Barrier	4	0.52-0.75	0.56	0.75	0.43
Image Barrier	3	0.77-0.88	0.78	0.87	0.68
Risk Barrier	5	0.08-0.94	0.81	0.87	0.62
Usage Barrier	4	0.74-0.87	0.83	0.89	0.66
Use Intention	3	0.93-0.96	0.94	0.96	0.90
Intention to Recommend	2	0.90-0.94	0.82	0.92	0.85
Inertia	4	0.68-0.78	0.78	0.82	0.53
Mistrust	4	0.77-0.84	0.83	0.88	0.65

Note. α = Cronbach's alpha, CR= Composite reliability, AVE= Average variance explained.

Table 4. Measurement properties of reflective constructs

The results indicated the alpha reliabilities for all the analysed variables were deemed to be within the acceptable range where α = >.70, except for the Tradition Barrier variable which was measured (α = .56). The Composite reliability for the study variables were found to be >0.70 for all the analysed constructs and was found to be within the acceptable range (Sarstedt et al., 2021). The values for the AVE for all the constructs were considered acceptable, with exception of the Tradition Barrier and Inertia. Furthermore, factor loading values for all the constructs were also deemed to be under the acceptable range as indicated in Table 4.

In addition to the validity and reliability assessments, the discriminant validity analyses were performed utilising the Fornell–Larcker criteria and Heterotrait–monotrait ratio (HTMT), as depicted in the below tables.

Variable	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8`*	*9*	*10*
Desirability	**0.92**									
Image Barrier	-0.70	**0.83**								
Inertia	-0.36	0.44	**0.73**							
Intention to Recommend	0.78	-0.66	-0.39	**0.92**						

Mistrust	-0.57	0.58	0.37	-0.61	**0.81**					
Risk Barrier	-0.49	0.52	0.25	-0.49	0.65	**0.79**				
Tradition Barrier	-0.32	0.43	0.35	-0.30	0.34	0.22	**0.65**			
Usage Barrier	-0.68	0.71	0.37	-0.68	0.56	0.45	0.34	**0.81**		
Use Intention	0.80	-0.73	-0.41	0.86	-0.63	-0.55	-0.36	-0.72	**0.95**	
Value Barrier	-0.71	0.63	0.34	-0.64	0.56	0.47	0.43	0.61	-0.68	**0.91**

Note. **p*<.05, ***p*<.01, ****p*<.001, Bold diagonal values indicate square root of AVE

Table 5. Discriminant validity of the measures (Fornell-Larcker criteria)

Variable	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*
Desirability	-											
Image Barrier	0.75	-										
Inertia	0.28	0.50	-									
Intention to Recommend	0.88	0.75	0.37	-								
Mistrust	0.58	0.62	0.37	0.67	-							
Risk Barrier	0.55	0.62	0.20	0.58	0.76	-						
Tradition Barrier	0.46	0.66	0.54	0.44	0.49	0.36	-					
Usage Barrier	0.76	0.85	0.35	0.80	0.62	0.52	0.50	-				
Use Intention	0.84	0.80	0.37	0.96	0.65	0.60	0.48	0.80	-			
Value Barrier	0.82	0.75	0.33	0.78	0.62	0.57	0.66	0.74	0.78	-		
DI x MT	0.30	0.13	0.21	0.33	0.15	0.06	0.13	0.18	0.24	0.21	-	
DI x IN	0.06	0.19	0.13	0.09	0.17	0.22	0.11	0.16	0.10	0.05	0.20	-

Table 6. Heterotrait-monotrait criteria (HTMT) a discriminant validity

The Fornell–Larcker criteria displayed in Table 5 of discriminant validity highlighted that the square-root values of the AVE were found to be consistently greater than the values of inter-construct correlation. No correlation was found to be greater than 0.85 and thus fulfils the validity requirements for the validity analysis (Fornell & Larcker, 1981; Kline, 2016). The second criteria of validity used was the Heterotrait–Monotrait criteria (HTMT) presented in Table 6. The values of each analysed construct should be less than 0.90 and the result of the analysis depicted in Table 6 showed that all the values were found to under the acceptable range (Sarstedt et al., 2021).

5.5. Assessment of Structural Model

Path	Direct effect	f^2	Bias-corrected CI	
	β		2.5% CI	97.5% CI
DI -> ITR	0.58***	0.60***	0.472	0.693
DI -> UI	0.38***	0.18*	0.236	0.524
IB -> UI	-0.15**	0.03	-0.252	-0.056
IN -> ITR	-0.11**	0.03	-0.199	-0.026
IN -> UI	-0.07	0.01	-0.153	0.012
MT -> ITR	-0.22***	0.09*	-0.307	-0.129
MT -> UI	-0.09	0.01	-0.192	0.004
RB -> UI	-0.10*	0.02	-0.177	-0.014
TB -> UI	0.00	0.00	-0.071	0.080
UB -> UI	-0.18***	0.05	-0.278	-0.078
VB -> UI	-0.07	0.01	-0.182	0.045
DI x MT -> ITR	-0.10*	0.03	-0.185	-0.018
DI x MT -> UI	-0.05	0.01	-0.127	0.036
DI x IN -> ITR	0.02	0.00	-0.055	0.091
DI x IN -> UI	-0.01	0.00	-0.079	0.050

Note. β = Beta, f^2= Cohen's f^2 for effect size, DI= Desirability, VB= Value Barrier, TB= Tradition Barrier, IB= Image Barrier, RB= Risk Barrier, UB= Usage Barrier, UI= Use Intention, ITR= Intention to Recommend, IN= Inertia, MT= Mistrust.

Table 7. Evaluation of structural model

As noted in Chapter 3, a structural model was developed and subsequently evaluated, and the theorised model was tested through structural equation modelling (SEM). A 5000 Bootstrap subsample, a common SEM resampling technique was employed to extrapolate and assess the validity of the proposed model. Sarstedt et al. (2019) suggests that the extrapolated bootstrapping values should be at least 500 subsamples, but that a 5000-subsample approach is ideal. The bootstrapping approach is a non-parametric technique which is generally employed for resampling purposes (Preacher & Hayes, 2008). This methodology is deemed to be suitable for samples that may violate normality assumptions (Sarstedt et al., 2021). Bootstrapping was thus employed and performed to achieve bias-correct bootstrap confidence intervals (Streukens & Leroi-Werelds, 2016). Table 7 represents the analysed path analysis and moderation analysis, as modelled, on each independent variable from the dependant variables.

5.6. Results of the PLS-SEM Statistical Analysis

The results of the PLS-SEM analysis revealed that the Use Barrier was found to be a significant negative predictor of Use Intention (B= -0.18, t= 3.57, p<.001), accepting **H1**. Tthe Value Barrier however, was found to be a non-significant predictor of Use intention (B= -0.07, t= 1.21, p=.226), rejecting **H2**. In comparison, the results showed that the Risk Barrier was found to be a significant negative predictor of Use intentions (B= -0.10, t= 2.28, p=.022), accepting **H3**.

Under the component of functional barriers, Use Barrier and Risk Barrier were found to significantly predict Use Intention and the relationship was found to be negative.

Under the component of Psychological Barriers, Tradition Barrier was found to be a non-significant predictor of Use Intention (B= 0.00, t= 0.04, p=.971), rejecting H4. In contrast, the Image Barrier was found to be a significant negative predictor of Use Intention (B= -0.15, t= 3.03, p=.002), accepting **H5**.

Inertia and Mistrust were found to be non-significant predictors of Use Intention (B= -0.07, t= 1.63, p=.103) and (B= -0.09, t= 1.85, p=.064) respectively, rejecting **H6** and **H8**. However, Inertia and Mistrust were found to be significant negative predictors of Intention to Recommend (B= -0.11, t= 2.59, p=.010) and (B= -0.22, t= 4.81, p<.001) accepting **H7** and **H9**.

Desirability was found to be a significant positive predictor of Intention to Recommend and Use Intention (B= 0.58, t= 10.30, p<.001), and (B= 0.388, t= 5.16, p<.001) respectively.

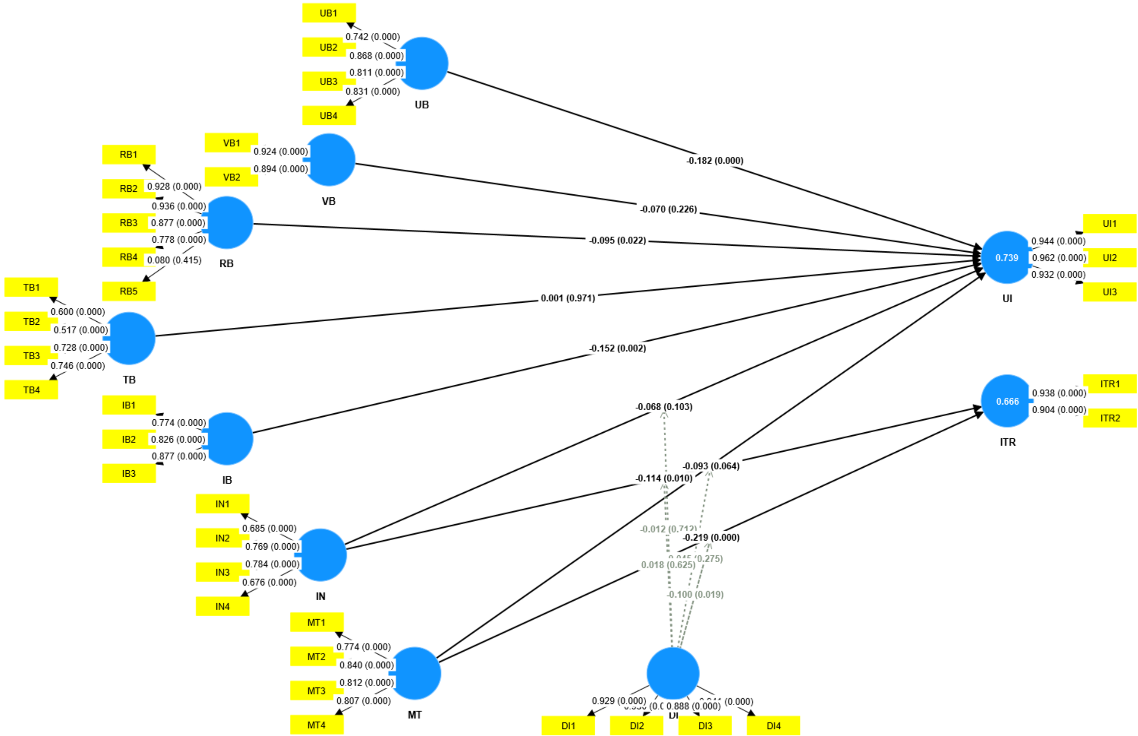

Figure 7. The statistical model results

5.7. Moderating Effect

It was hypothesised that Desirability is likely to moderate the relationship between Inertia and Mistrust and that the dependent variables Use Intention and Intention to Recommend, the results shown within Table 7, that there was found to be a moderating effect of Desirability between Mistrust and Intention to Recommend (B= -0.10, t= 2.35, p=.019) thereby accepting **H10**, the results showed that the moderating effect was found to be less negative and indicated that the interaction between Desirability and Mistrust decreased Intention to Recommend significantly (Figure 8).

However, no moderating effect of desirability was noted between the other variables as shown (Table 7), resulting in the rejection of **H11**, **H12**, and **H13** relating to the moderation hypotheses.

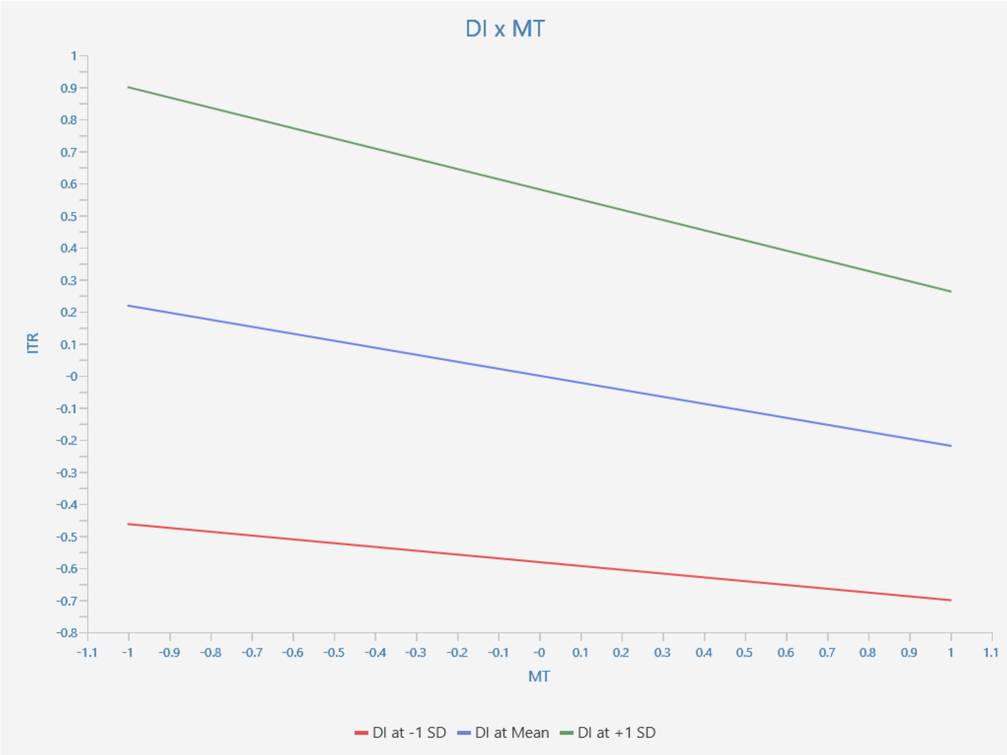

Figure 8. Simple slope

5.8. Predictive relevance and predictive power

Q^2 is an index that estimates the predictive relevance of the evaluated model in PLS-based SEM. Q^2 indicates the ability of the tested model to predict the outcome variable accurately based on the predictor variables used in the analysed model. The Q^2 value ranges from 0 to 1. A value of 0 and close to 0 indicates no predictive or low predictive relevance, whereas a value of 1 or close to 1 indicates higher predictive relevance in the model.

The coefficient of determination R^2 is used to determine the predictive power of the structural model, which is the total or combined effect of independent variables on the dependent variables (Tenenhaus et al., 2005). The guidelines recommended by Sarstedt et al. (2017) in relation to the values of R^2 should be 0.25, 0.50, and 0.75 which refer to weak, moderate, and strong predictive powers, respectively. Chin (1998) on the other hand, suggested that the values of R^2 at 0.67, 0.33, and 0.19 are substantial, moderate, and weak predictive powers, respectively.
Table 4.6 below illustrates the predictive relevance and predictive power of independent variables on the dependent variables in the model.

Independent Variables	Dependant Variables	Q^2	R^2
Usage Barrier Value Barrier Risk Barrier Tradition Barrier Image Barrier Inertia Mistrust	Use Intention	0.71	0.74***
Inertia Mistrust	Intention to Recommend	0.65	0.67***

Figure 9. Predictive relevance and power of the variables

5.9. Conclusion

This chapter presented the results of the data tests and final analysis collected as part of the primary data collection process. Various validity and reliability tests were conducted to confirm the aptness of the results before the PLS-SEM analysis, which was used to accept or reject the formulated hypotheses, was performed. Furthermore, a predictive model was simulated to find the predictive relevance and power of the independent variables on the dependent variables.

The results concluded that 6 hypotheses were accepted and 7 were rejected and there was a significant predictive relevance and power within the variable construct. The moderation impact of Desirability was found to influence only one relationship between Mistrust and the Intention to Recommend.

6. Chapter Six: Discussion of Results

6.1. Introduction

This chapter includes the discussion of results which were noted in Chapter 5. A summary of the research results is provided, and the outcome is then reviewed against the literature analysed in Chapter 2.
The statistical tools are discussed, and the statistical tests and outputs are reviewed.

6.2. Summary of Research Results

#	Hypothesis	Test Result	Outcome
H_1	Usage barriers are negatively correlated with the use intention towards FRPS.	Significant negative predictor.	Accepted
H_2	Value barriers are negatively correlated with the use intention towards FRPS.	Non-significant predictor.	Rejected
H_3	*Risk barriers are negatively correlated with the use intention towards FRPS.*	Significant negative predictor.	Accepted
H_4	*Tradition barriers are negatively correlated with the use intention towards FRPS.*	Non-significant predictor.	Rejected
H_5	*Image barriers are negatively correlated with the use intention towards FRPS.*	Significant negative predictor.	Accepted
H_6	*Inertia is negatively correlated with the use intention towards FRPS*	Non-significant predictor.	Rejected
H_7	*Inertia is negatively correlated with the intention to recommend FRPS.*	Significant negative predictor.	Accepted

$\boldsymbol{H_8}$	*Mistrust is negatively correlated with the use intention towards FRPS.*	Non-significant predictor.	Rejected
$\boldsymbol{H_9}$	*Mistrust is negatively correlated with the intention to recommend FRPS.*	Significant negative predictor.	Accepted
$\boldsymbol{H_{10}}$	*Desirability has a moderating effect on Inertia and the use intentions of FRPS.*	No moderating effect.	Rejected
$\boldsymbol{H_{11}}$	*Desirability has a moderating effect on Inertia and the Intention to Recommend FRPS.*	No moderating effect.	Rejected
$\boldsymbol{H_{12}}$	*Desirability has a moderating effect on Mistrust and the use intentions of FRPS.*	No moderating effect.	Rejected
$\boldsymbol{H_{13}}$	*Desirability has a moderating effect on Mistrust and the Intention to Recommend FRPS.*	Moderating effect.	Accepted

Table 8. Summary of Hypotheses Outcomes

6.3. Data Collected and Demographics

A total of 303 responses were collected and deemed valid for the analysis. This number was significantly greater than the 138 samples that was recommended in Chapter 4.6. The larger sample was assumed to stem from the snowball sampling technique and sharing of the survey via online and social media channels.

The analysis of demographics within the base reflects the concentration risk raised as part of the sampling methodology chapter. Whilst the gender split was relatively equal in Table 14 (53% Female, 46% Male, 1% Other), there is evidence in Table 13 of higher concentration of respondents between 26-45 (74%) which may have contributed to rejection of Hypotheses **H2, H4, H6, H8** (Owusu et al., 2021).

Furthermore, there is a high concentration of respondents who indicated holding a tertiary qualification or higher (88%) which is not considered representative of the population (OECD Data, 2023).

6.4. Discussion of Hypothesis Test Results

6.4.1. Hypothesis 1

H_1 considered the inhibition Usage Barriers would have on consumers' Use Intention of FRPS.

> *H_1: Usage barriers are negatively correlated with the use intention towards FRPS.*

The results of the PLS-SEM analysis revealed that the Usage Barrier was found to be a significant negative predictor of Use Intention (B= -0.18, t= 3.57, p<.001), thereby accepting H_1.

Consumers' intention to use innovation and technology is often influenced by how the technology or innovation aligns with existing workflows, habits, or consumer practices (Ram & Sheth, 1989). Innovation that requires significant change to the current process is met with resistance (Heidenreich & Handrich, 2015).
In the context of FRPS, the consumers' resistance to adopting the innovation is influenced by perceived Usage Barriers, meaning consumers perceive FRPS to require significant change to their current practice to utilise the service and is likely to be a significant inhibitor to the adoption of FRPS.

The acceptance of H_1 supports the IRT notion that Usage Barriers are significant predictors of Consumer Inhibition and will be a likely barrier for adoption.

6.4.2. Hypothesis 2

H_2 considered the inhibition Value Barriers would have on consumers' Use Intention of FRPS.

H_2: Value barriers are negatively correlated with the use intention towards FRPS.

The results of the PLS-SEM analysis revealed that Value Barriers were a non-significant predictor of Use intention (B= -0.07, t= 1.21, p=.226), rejecting H_2.

Value barriers to adoption of an innovation is strongly related to the value the innovation delivers. To drive adoption of the innovation, significant value must be perceived by the consumer. If no value is perceived, then the incentive for a customer to adopt is significantly reduced. Morar (2013) found that consumers weigh up value of a system based on various factors, but overall, the positive value of a system must outweigh the perceived cost to encourage adoption and use.

The absence of a significant predictor in terms of Value Barrier and Use Intention indicates that the perception of FRPS as a value adding service might not be fully understood amongst the respondents.

Further investigation into the impact of Value Barriers could thus be suggested for future research.

6.4.3. Hypothesis 3

H_3 considered the inhibition Risk Barriers would have on consumers' Use Intention of FRPS.

H_3: Risk barriers are negatively correlated with the use intention towards FRPS.

The results of the PLS-SEM analysis revealed that Risk Barriers were found to be a significant negative predictor of Use intentions (B= -0.10, t= 2.28, p=.022), thereby accepting H_3.

Risk barriers have been a considerable consideration in influencing consumers' willingness to adopt FRPS. Within the context of technology adoption, the acceptance of innovation is influenced by levels of uncertainties introduced by the innovation in question (Dunphy & Herbig, 1995). Applying this lens to the realm FRPS, the concerns pertaining to uncertainties and risk introduced by FRPS have been a focal point for previous studies relating to data privacy (Liu et al., 2021) and technology risk (De Kerviler et al., 2016).

The results of this study confirm that the consumers' perception risk barriers relating to data privacy risk and technology risk are prevalent in FRPS.

The acceptance of H_3 supports the IRT framework that Risk Barriers are significant predictors of consumer inhibition and will likely be a barrier for adoption. The acceptance further illustrates that privacy risk will continue to be a significant factor and inhibitor in adopting FRPS (Liu et al., 2021; X. Yang et al., 2023). These risks and uncertainties will thus continue (Dunphy & Herbig, 1995)until such a time that stakeholders within the FRPS can address these uncertainties and allay the concerns of the consumer (Ram & Sheth, 1989).

As risk is a broad topic, and most of the research has focused on privacy risk in relation to FRPS, further research may be required to gain insight into other risk factors that may influence a consumer's intention to utilise FRPS.

6.4.4. Hypothesis 4

H_4 considered the inhibition Tradition Barriers would have on consumers' Use Intention of FRPS.

> H_4: *Tradition barriers are negatively correlated with the use intention towards FRPS.*

The results of the PLS-SEM analysis revealed that Tradition Barrier was found to be a non-significant predictor of Use Intention (B= 0.00, t= 0.04, p=.971), rejecting H_4.

The psychological barrier associated with Tradition, is related the cultural change that is introduced to the consumer by the innovation (El Badrawy et al., 2012). When an innovation requires deviation from existing tradition or practices, it is generally resisted. It has been shown that the greater the deviation from traditional practice, the greater the resistance level observed (John & Klein, 2003).

It has been noted that the current payment processes are very well entrenched in society globally, with card and cash payments leading the way. These mechanisms do not require biometric intervention, and the current processes are well accepted and entrenched with consumers.

The rejection of H_4 is interesting as it indicates that consumers may view FRPS as a minor deviation in payment practice compared to existing practices such as cash and card payments and thus do not view Tradition Barriers as inhibitors to use the service.

Whilst H_4 is rejected in principle, further research may consider exploring the Tradition Barrier in relation to a single existing payment form factor.

6.4.5. Hypothesis 5

H_5 considered the inhibition Image Barriers would have on consumers' Use Intention of FRPS.

> H_5*: Image barriers are negatively correlated with the use intention towards FRPS.*

The results of the PLS-SEM analysis revealed that Image Barrier was found to be a significant negative predictor of Use Intention (B= -0.15, t= 3.03, p=.002), accepting H_5.

The Image Barrier is a perceptual problem that arises from stereotypical thinking and is a significant challenge for innovation in terms of consumer adoption. The perceptions formed about an innovation can significantly affect the adoption by the consumer (Lian & Yen, 2013). In terms of FRPS, the Image Barrier is related to the perception of how FRPS is perceived by the consumer in terms of the complexity, and whether the service is perceived positively or negatively.

As image and perception is a broad topic, further investigation may be required to further explain how Image is inhibiting the adoption of FRPS.

6.4.6. Hypothesis 6

H_6 considered the inhibition Inertia would have on consumers' Use Intention of FRPS.

H_6: Inertia is negatively correlated with the use intention towards FRPS.

The results of the PLS-SEM analysis revealed that Inertia was found to be a non-significant predictor of Use Intention (B= -0.07, t= 1.63, p=.103), rejecting H_6.

The resistance to change that consumers face in making technology-use decisions is likely to be higher when factors relating to Inertia are evident (Samuelson & Zeckhauser, 1988).
The rejection of H_6 is then considered somewhat surprising, given the acceptance of the related H_7 below and is perhaps indicative that consumers' levels of inertia are beginning to decrease and are becoming more open to accepting FRPS.

6.4.7. Hypothesis 7

H_7 considered the inhibition Inertia would have on consumers Intention to Recommend FRPS.

H_7: Inertia is negatively correlated with the intention to recommend FRPS.

The results of the PLS-SEM analysis found Inertia to be significant negative predictors of Intention to Recommend (B= -0.11, t= 2.59, p=.010) and accepting, H_7.

The acceptance of H_7 illustrative of could potentially illustrate that whilst consumers levels of Inertia when faced with Use Intention may be decreasing as argued in 6.5.6, their Intention to Recommend may require attention to drive the repeat behaviour and lower their levels of Inertia to drive recommendation intention.

Whilst the examination of the IRT construct remains valid and is supported by the outcome of this hypothesis, examination of the relationship between UI and ITR is required to further explain the user behaviour in the instance of Inertia.

6.4.8. Hypothesis 8

H_8 considered the inhibition Mistrust would have on consumers' Use Intention.

H_8: Mistrust is negatively correlated with the use intention towards FRPS.

The results of the PLS-SEM analysis found Mistrust to be a non-significant predictor of Use Intention (B= -0.09, t= 1.85, p=.064), rejecting H_8.

The rejection of H_8 may indicate decreasing levels of mistrust pertaining to FRPS amongst the respondents. This may further indicate that consumers are becoming more proficient in terms of payment innovation and are becoming more prepared to take on FRPS as a payment method (Mysen et al., 2011).

The rejection of this hypotheses may also be related to the higher concentration of younger, educated respondents as indicated within the demographic analysis of the study as youth and education has been shown to drive higher levels of technology adoption (Abu-Shanab, 2011; Owusu et al., 2021).

6.4.9. Hypothesis 9

H_9 considered the inhibition of Mistrust on consumers Intention to Recommend FRPS.

H_9: Mistrust is negatively correlated with the intention to recommend FRPS.

The results of the PLS-SEM analysis found Mistrust to be a significant negative predictor of Intention to Recommend (B= -0.22, t= 4.81, p<.001) accepting, H_9.

The acceptance of H_9 is somewhat unexpected, given the rejection of H_8 in 6.5.8 above. Mistrust has been noted to hinder technology adoption and increase reluctance to use and recommend the associated services (Parasuraman, 2000). The analysis results associated with H_9 may indicate that whilst mistrust is decreasing, the intention to recommend a technology further than one's use remains prevalent.

6.4.10. Hypothesis 10

H_{10} considered the moderating effect that Desirability would have on the relationship between Inertia and Use Intention,

> H_{10}*: Desirability has a moderating effect on Inertia and the use intentions of FRPS.*

The results shown (Table 7) that there was found to be a moderating effect of Desirability between the Mistrust and Intention to Recommend (B= -0.10, t= 2.35, p=.019) accepting H_{10}.

6.4.11. Hypothesis 11-13

H_{11} considered the moderating effect that Desirability would have on the relationship between Inertia and Intention to Recommend

> H_{11}*: Desirability has a moderating effect on Inertia and the Intention to Recommend FRPS.*

H_{12} considered the moderating effect that Desirability would have on the relationship between Inertia and Intention to Recommend

> H_{12}*: Desirability has a moderating effect on Inertia and the Intention to Recommend FRPS.*

H_{13} considered the moderating effect that Desirability would have on the relationship between Inertia and Intention to Recommend

> H_{13}*: Desirability has a moderating effect on Inertia and the Intention to*

Recommend FRPS.

Whereas no moderating effect of desirability was found between other variables as shown (Table 7), resulting in the rejection of H_{11}, H_{12}, H_{13}.

The rejection of these Hypotheses contradicts the reviewed literature, which noted that DI significantly influenced UI in prior studies (Morar, 2013) and does not support the perception that Perceived Desirability influences UI under the TADU model as described by (Moghavvemi et al., 2017).

6.5. Summary of the Hypothesis Test Results

In total, the research concluded that six of the formulated hypotheses were accepted and seven hypotheses were rejected.
The analysis of the research indicates that consumers are resistant to use FRPS given concerns related to Usage, Risk, and Image Barriers. Moreover, Inertia and Mistrust are shown to be significant inhibitors relating to the intention to recommend. The role of Desirability as a moderating factor was noted to have a moderating effect on Mistrust and the Intention to Recommend.

6.6. Conclusion

The sixth chapter discusses the results of the data canalised in the fifth chapter. The results were noted to be relatively consistent upon the theories on which they were based but do contain some surprising results which need to be further researched to explain the degree to which the inhibition is relevant.

7. Chapter Seven: Conclusion and Recommendations

7.1. Introduction

The research study primary aim was to determine potential inhibiting factors that may be relevant toward the technological adoption of FRPS of consumers as set out in the primary research question in Chapter 1. A review of existing literature was

discussed in Chapter 2, where the relevance of IRT barriers and the Inertia and Mistrust variables were deemed to provide the constructs utilised in the research framework underpinning this study. Chapter 3 introduced the conceptual model, elaborated on the research questions in scope and presented the hypotheses to be analysed. Chapter 4 set out the research methodology and the results were subsequently presented in Chapter 5 and discussed in Chapter 6.
The final Chapter sets out the principal conclusions, followed by theoretical and practical contributions before concluding with research limitations and recommendations for future research.

7.2. Principal Conclusions

The relevance of FRPS at a global level is significant as payment systems evolve beyond physical form factors into the realm of biometrics, creating an opportunity to transform consumers' payment experience (Visa Navigate, 2021). FRPS has seen usage rise considerably in recent time, with the Eastern countries showing significant growth relative to their Western counterparts (Dialani, 2019; Luo & Guo, 2021).

The study set out to identify potential inhibitors to users' adoption and use of FRPS utilising constructs of IRT, TAM and UTAUT.
IRT provided a valuable framework to understand the functional and psychological barriers that would influence a user’s intention to use and recommend FRPS, whilst the extension of research and inclusion of variables from TAM and UTAUT provided further insights into the impact of external and moderating factors.

Existing literature alluded to consumers’ adoption of FRPS primarily linked to perceived usefulness and privacy impact which has been explored utilising adoption frameworks such as TAM and UTAUT.

The study principally concludes that IRT remains reliable predictor of consumers inhibition to adopt technology, and in the context of this study, both functional and psychological barriers have an influence on the consumers intention to utilise FRPS.

Furthermore, we note that Inertia and Mistrust both influence consumers Intention to Recommend FRPS and will be a critical area to explore if we are to gain further insight into consumers resistance to recommend FRPS as a service.

7.3. Theoretical Contribution

The study of resistance to technology adoption has been studied broadly as evidenced by the existing literature. This study adds to the body of existing research relating to resistance of technology adoption and further contributes to the growing realm of FRPS by analysing potential inhibitors to technology adoption of consumers. While significant research focuses on technology adoption, little research has been conducted to gain insight into the resistance and potential inhibitors in this space. The results presented in this study therefore contribute to the theoretical understanding of inhibitors of consumer adoption relating to FRPS.

7.4. Implications for Business, Management, and other Stakeholders

The understanding of consumer adoption of FRPS is critical for businesses, management, and other various stakeholders due to the transformative impact it has on the way transactions are conducted. FRPS has the potential to streamline and enhance the payment process by offering a convenient and secure alternative to traditional payment methods. The insights revealed in this survey will assist stakeholders to align their strategies to meet the evolving needs of their consumers. This is deemed critical to drive repeat consumer behaviour which increases customer satisfaction and loyalty.
Furthermore, the successful implementation of FRPS can lead to operational efficiencies, cost savings and a competitive edge in the market. Businesses that adopt and optimise FRPS before their competition may result in a competitive advantage. Effective management requires a proactive approach to understand their consumer dynamics and adjust their strategies accordingly with the wants and needs of their target audience, therefore those businesses that can understand consumers inhibitors to adoption of FRPS will be able to work on strategies that overcome such inhibition to adoption (Ram & Sheth, 1989).

Adopting FRPS can have implications for various stakeholders beyond just businesses and management. Some identified key stakeholders that could be impacted or informed by this research extends below.

Government bodies and regulatory agencies are crucial in overseeing and setting guidelines for emerging technologies, which includes FRPS. It is critical that these institutions comprehend the implications and concerns FRPS introduces into the market. Moreover, compliance with privacy and security regulations is maintained, and therefore businesses must keep abreast of any legal developments in this area to ensure adherence to applicable laws.

Since FRPS involves biometric data, privacy advocates and consumer rights groups may closely monitor its adoption. Transparency in data usage, consent mechanisms, and safeguards against potential misuse are critical aspects that these stakeholders may be concerned about, and therefore, this research would aid in identifying and understanding concerns consumers may have in terms of FRPS.

FRPS requires advancement and innovation in technology. Therefore, companies that specialise in providing facial recognition technology solutions are directly impacted by the adoption of facial recognition payments. The developed technologies must be robust, secure, and compliant with all relevant regulations. Understanding market demands and consumer preferences is essential for continuous improvement and innovation in their offerings.

Banks and financial institutions are integral to the payment ecosystem globally. These institutions may need to adapt their infrastructure and processes to accommodate FRPS. Understanding consumer inhibition in payments is crucial for financial institutions to offer relevant and competitive services aligned with their consumers' expectations.

As consumer behaviour evolves, marketing and advertising agencies must adjust their strategies to effectively reach and engage audiences using new payment methods. Understanding how consumers adopt or resist FRPS can inform targeted marketing campaigns.

By considering the insights and perspectives of this study, these stakeholders can navigate the landscape of FRPS more effectively and build a foundation of trust and support within the broader ecosystem.

7.5. Research Limitations

Several vital limitations were noted in this study. The cross-sectional timeline of the study hindered the depth of analysis and further impacted the number and nature of responses collected for the analysis.

The non-probability snowball sampling technique exposed the study to a higher concentration risk of respondents with high degrees of similarity, which could impact the analysis results. Upon review of the descriptive statistics, it was noted that a significant portion of the respondents fell within the lower age groups, which could influence the results as youth are less resistant to adopting technology (Owusu et al., 2021).

7.6. Recommendations for Future Research

This study identifies potential inhibitors which may affect the adoption of FRPS in consumers. The bulk of research has been conducted on Eastern consumers. Thus, future research recommendations would include exploring cultural and regional variances which has not yet been considered.

This research considers IRT, TAM and UTAUT elements along with SQB. External factors such as gender, age, and education levels were not factored into the conceptual model and would provide further insight into which consumers are more prone to adopt or reject based on these external factors.

The conceptual design of the model did not take into consideration consumer use channels such as in-store vs online usage, which opens further recommendations for future studies to explore.

7.7. Conclusion

The research study primary aim was to determine potential inhibiting factors that may be relevant toward the technological adoption of FRPS of consumers. Considering the reviewed literature, research hypotheses formulated in conjunction with the conceptual framework, data gathered and the analysis of the results, it was noted that the sample data indicated significant inhibition to the adoption of FRPS. The data further indicated that there was a significant degree of predictability relating to the adoption of FRPS based on the user's perception of the technology thereby supporting IRT within the context of FRPS.

The study concludes that both functional and psychological barriers influence consumers inhibition to adopt and use FRPS.

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Appendix A: Questionnaire

<u>Section 1: Informed Consent</u>

Inhibitors to the adoption of facial recognition payments.

Dear Participant,

I am a student at the Gordon Institute of Business Science, affiliated with the University of Pretoria. I invite your participation in this survey, a key component of my MBA research.

This study focuses on factors that may inhibit a consumer from utilising facial recognition payment systems. As technology advances and consumer behaviours change, payment systems must keep up with the pace of innovation to provide seamless, secure and efficient transactions. Privacy concerns, ease of use, and data security concerns are some of the inhibitors that can be noted as deterrents, or inhibitors to consumer adoption in terms of biometric payments. This study aims to test these various inhibiting factors of consumers in the field of facial recognition payments.

The survey is designed to take approximately 10 minutes to complete. I assure you that your participation is entirely **anonymous and voluntary**, and you are free to withdraw from the research at any point without consequence. While your responses will remain confidential, it's important to note that aggregated results may be shared. By completing this survey, you signify your voluntary engagement in this research. Your insights and contributions are immensely valued, and I extend my heartfelt gratitude for your time and willingness to participate.

For any queries regarding this research, please reach out to:

Researcher:

Craig Goodwin

21752266@mygibs.co.za

Research Supervisor:

Dr Christian Osakwe

OsakweC@gibs.co.za

Section 2: Demographics

Age
Mark only one oval.

- 18 - 25
- 26 - 35
- 36 - 45
- 46 - 55
- 56 - 64
- >65

Gender
Mark only one oval.

- Female
- Male
- Other
- Prefer Not To Disclose

Education
Mark only one oval.

- Primary
- Secondary
- Vocational
- Tertiary
- Postgraduate or Higher

Occupational Status
Mark only one oval.

- Employed
- Self-Employed
- Unemployed
- Student

Retired

Personal Income (Gross Amount)
Mark only one oval.

R1 - –237,000

R237,001 - –370,500

R370,501 - –512,800

R512,801 - –673,000

R673,001 - –857,900

R857,900 - –1,817,000

> R1,817,001

Prefer Not To Disclose

Section 3: Desirability

Using facial recognition payments services is a good idea. *
Mark only one oval.

Strongly Agree

Agree

Neither Agree nor Disagree

Disagree

Strongly Disagree

Using facial recognition payment services is advisable. *
Mark only one oval.

Strongly Agree

Agree

Neither Agree nor Disagree

Disagree

Strongly Disagree

Using facial recognition payment services is pleasant. *
Mark only one oval.

- Strongly Agree
- Agree
- Neither Agree nor Disagree
- Disagree
- Strongly Disagree

I will enjoy using facial recognition payment services. *
Mark only one oval.

- Strongly Agree
- Agree
- Neither Agree nor Disagree
- Disagree
- Strongly Disagree

Section 4: Value Barriers

In my opinion, Facial Recognition Payments does not offer any advantage compared to handling my payments in other ways.
Mark only one oval.

- Strongly Agree
- Agree
- Neither Agree nor Disagree
- Disagree
- Strongly Disagree

In my opinion, the use of Facial Recognition Payments decreases my ability to control my financial matters by myself.
Mark only one oval.

- Strongly Agree
- Agree
- Neither Agree nor Disagree
- Disagree

Strongly Disagree

Section 5: Tradition Barriers

I prefer paying with cash. *
Mark only one oval.

Strongly Agree

Agree

Neither Agree nor Disagree

Disagree

Strongly Disagree

I think that cash gives a better feeling of my financial means.
Mark only one oval.

Strongly Agree

Agree

Neither Agree nor Disagree

Disagree

Strongly Disagree

I prefer paying with card.
Mark only one oval.

Strongly Agree

Agree

Neither Agree nor Disagree

Disagree

Strongly Disagree

I think that card gives a better feeling of my financial means. *
Mark only one oval.

Strongly Agree

Agree

- Neither Agree nor Disagree
- Disagree
- Strongly Disagree

Section 6: Image Barriers

In my opinion, new technology is often too complicated to be useful.
Mark only one oval.

- Strongly Agree
- Agree
- Neither Agree nor Disagree
- Disagree
- Strongly Disagree

I have a view that Facial Recognition Payments services are difficult to use.
Mark only one oval.

- Strongly Agree
- Agree
- Neither Agree nor Disagree
- Disagree
- Strongly Disagree

In general, I have a negative image of the Facial Recognition Payments.
Mark only one oval.

- Strongly Agree
- Agree
- Neither Agree nor Disagree
- Disagree
- Strongly Disagree

Section 7: Risk Barriers

I am concerned about how my data is stored for a Facial Recognition Payments.

Mark only one oval.

- Strongly Agree
- Agree
- Neither Agree nor Disagree
- Disagree
- Strongly Disagree

I am concerned about how my data is used for Facial Recognition Payments.
Mark only one oval.

- Strongly Agree
- Agree
- Neither Agree nor Disagree
- Disagree
- Strongly Disagree

I am concerned about the possibility of personal data theft when using Facial Recognition Payments.
Mark only one oval.

- Strongly Agree
- Agree
- Neither Agree nor Disagree
- Disagree
- Strongly Disagree

I am concerned about technological errors (e.g., data not detected) when using Facial Recognition Payments.
Mark only one oval.

- Strongly Agree
- Agree
- Neither Agree nor Disagree
- Disagree

Strongly Disagree

I am concerned about the low number of sites accepting facial recognition payments.
Mark only one oval.

- Strongly Agree
- Agree
- Neither Agree nor Disagree
- Disagree
- Strongly Disagree

Section 8: Usage Barriers

Using Facial Recognition Payments would not make it more effective for me to pay for items.
Mark only one oval.

- Strongly Agree
- Agree
- Neither Agree nor Disagree
- Disagree
- Strongly Disagree

Using Facial Recognition Payments will not enhance my shopping effectiveness.
Mark only one oval.

- Strongly Agree
- Agree
- Neither Agree nor Disagree
- Disagree
- Strongly Disagree

Using Facial Recognition Payments is not straightforward.
Mark only one oval.

- Strongly Agree
- Agree

- Neither Agree nor Disagree
- Disagree
- Strongly Disagree

Using Facial Recognition Payments is not convenient.
Mark only one oval.

- Strongly Agree
- Agree
- Neither Agree nor Disagree
- Disagree
- Strongly Disagree

Section 9: Intention to Use & Recommend Facial Recognition Payments

I intend to use Facial Recognition Payments in the next months.
Mark only one oval.

- Strongly Agree
- Agree
- Neither Agree nor Disagree
- Disagree
- Strongly Disagree

I will try to use Facial Recognition Payments in my daily life.
Mark only one oval.

- Strongly Agree
- Agree
- Neither Agree nor Disagree
- Disagree
- Strongly Disagree

Interacting with my financial account over Facial Recognition Payments is something that I would do.

Mark only one oval.

- Strongly Agree
- Agree
- Neither Agree nor Disagree
- Disagree
- Strongly Disagree

I will recommend the Facial Recognition Payments to my friends.
Mark only one oval.

- Strongly Agree
- Agree
- Neither Agree nor Disagree
- Disagree
- Strongly Disagree

If I have a good experience with the Facial Recognition Payments, I will recommend it to my friends.
Mark only one oval.

- Strongly Agree
- Agree
- Neither Agree nor Disagree
- Disagree
- Strongly Disagree

Section 10: Inertia

I generally consider change as a negative thing.
Mark only one oval.

- Strongly Agree
- Agree
- Neither Agree nor Disagree
- Disagree

Strongly Disagree

I'd rather do the same old things than try new ones.
Mark only one oval.

- Strongly Agree
- Agree
- Neither Agree nor Disagree
- Disagree
- Strongly Disagree

In my opinion, existing payment methods are satisfactory.
Mark only one oval.

- Strongly Agree
- Agree
- Neither Agree nor Disagree
- Disagree
- Strongly Disagree

In general, I resist change.
Mark only one oval.

- Strongly Agree
- Agree
- Neither Agree nor Disagree
- Disagree
- Strongly Disagree

Section 11: Mistrust

I think that Facial Recognition Payments is unreliable.
Mark only one oval.

- Strongly Agree
- Agree

Neither Agree nor Disagree

Disagree

Strongly Disagree

Companies that use Facial Recognition Payments only want to make money with our data.
Mark only one oval.

Strongly Agree

Agree

Neither Agree nor Disagree

Disagree

Strongly Disagree

Companies that use Facial Recognition Payments do what they want with our data.
Mark only one oval.

Strongly Agree

Agree

Neither Agree nor Disagree

Disagree

Strongly Disagree

I assume that companies that use Facial Recognition Payments are only interested in their benefits, not mine.
Mark only one oval.

Strongly Agree

Agree

Neither Agree nor Disagree

Disagree

Strongly Disagree

Appendix B: Ethical Clearance Approval

Ethical Clearance Urgent Rework Required

MR

Masters Research <MastersResearch@gibs.co.za>

To: 21752266@mygibs.co.za; **Cc:** Masters Research

Monday, 04 September 2023 at 19:55

Gordon Institute of Business Science
University of Pretoria

Ethical Clearance Conditionally Approved

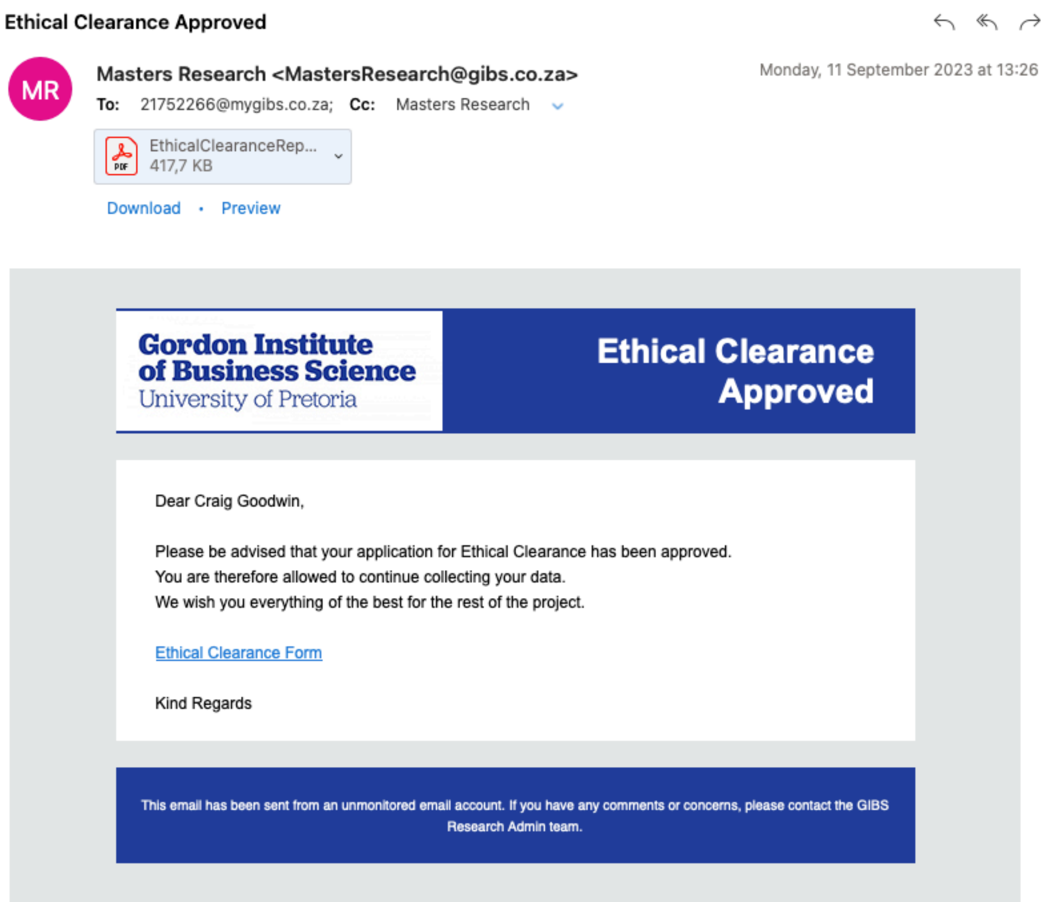
Dear Craig Goodwin,
Please be advised that your application for Ethical Clearance has been approved subject to the following conditions.
Re: 25: include information on how data will be stored
Once you have made this minor amendment and kindly resubmit your application
We wish you everything of the best for the rest of the project.

Ethical Clearance Form

Kind Regards

This email has been sent from an unmonitored email account. If you have any comments or concerns, please contact the GIBS Research Admin team.

Figure 10. Ethical Clearance Conditional Approval



Ethical Clearance Approved

Masters Research <MastersResearch@gibs.co.za>

Monday, 11 September 2023 at 13:26

To: 21752266@mygibs.co.za; Cc: Masters Research

EthicalClearanceRep...
417,7 KB

Download • Preview

Gordon Institute of Business Science
University of Pretoria

Ethical Clearance Approved

Dear Craig Goodwin,

Please be advised that your application for Ethical Clearance has been approved.
You are therefore allowed to continue collecting your data.
We wish you everything of the best for the rest of the project.

Ethical Clearance Form

Kind Regards

This email has been sent from an unmonitored email account. If you have any comments or concerns, please contact the GIBS Research Admin team.

Figure 11. Ethical Clearance Final Approval

Appendix C: Code Book

QUESTION	ITEM LABEL	POSSIBLE ANSWERS	CODE
AGE	Age	18-25	1
		26-35	2
		36-45	3
		46-55	4
		56-65	5
		>65	6
GENDER [FEMALE, MALE, OTHER, NOT TO SHOW]	Gender	Female	1
		Male	2
		Other	3
		Prefer Not To Disclose	4
EDUCATION [PRIMARY, SECONDARY, VOCATIONAL, TERTIARY, HIGHER]	Education	Primary	1
		Secondary	2
		Vocational	3
		Tertiary	4
		Higher	5
OCCUPATIONAL STATUS [WORKING, JOBLESS, STUDENT, RETIRED]	Occupation	Employed	1
		Unemployed	2
		Self-Employed	3
		Student	4
		Retired	5
PERSONAL INCOME (APPROXIMATE GROSS AMOUNT)	Income	R1 - R237,000	1
		R237,001 - R370,500	2
		R370,501 - R512,800	3
		R512,801 - R673,000	4
		R673,001 - R857,900	5
		R857,900 - R1,817,000	6
		> R1,817,001	7
		Prefer Not To Disclose	8
LIKERT SCALE RESPONSES		Strongly Agree	1
		Agree	2
		Neither Agree Nor Disagree	3
		Disagree	4
		Strongly Disagree	5

Appendix D: Descriptive Statistics

D1		D2		D3		D4		D5	
Age		*Gender*		*Education*		*Occupational Status*		*Income*	
Mean	3,00990099	Mean	1,46534653	Mean	4,37417219	Mean	1,49006623	Mean	5,67666667
Standard Errc	0,05959325	Standard Errc	0,02908083	Standard Errc	0,0525178	Standard Errc	0,0605678	Standard Errc	0,12826067
Median	3	Median	1	Median	5	Median	1	Median	6
Mode	3	Mode	1	Mode	5	Mode	1	Mode	6
Standard Dev	1,0373334	Standard Dev	0,50620697	Standard Dev	0,91266202	Standard Dev	1,05255613	Standard Dev	2,22153994
Sample Varia	1,07606059	Sample Varia	0,25624549	Sample Varia	0,83295197	Sample Varia	1,10787441	Sample Varia	4,93523969
Kurtosis	0,89399454	Kurtosis	-1,7672415	Kurtosis	1,45760873	Kurtosis	3,45546781	Kurtosis	-0,2719428
Skewness	0,87598352	Skewness	0,21669637	Skewness	-1,5233051	Skewness	2,09993615	Skewness	-0,8787471
Range	5	Range	2	Range	3	Range	4	Range	7
Minimum	1	Minimum	1	Minimum	2	Minimum	1	Minimum	1
Maximum	6	Maximum	3	Maximum	5	Maximum	5	Maximum	8
Sum	912	Sum	444	Sum	1321	Sum	450	Sum	1703
Count	303	Count	303	Count	302	Count	302	Count	300
Confidence L	0,11727058	Confidence L	0,05722672	Confidence L	0,10334854	Confidence L	0,11918995	Confidence L	0,25240797

Figure 12. Descriptive Statistics: Demographics

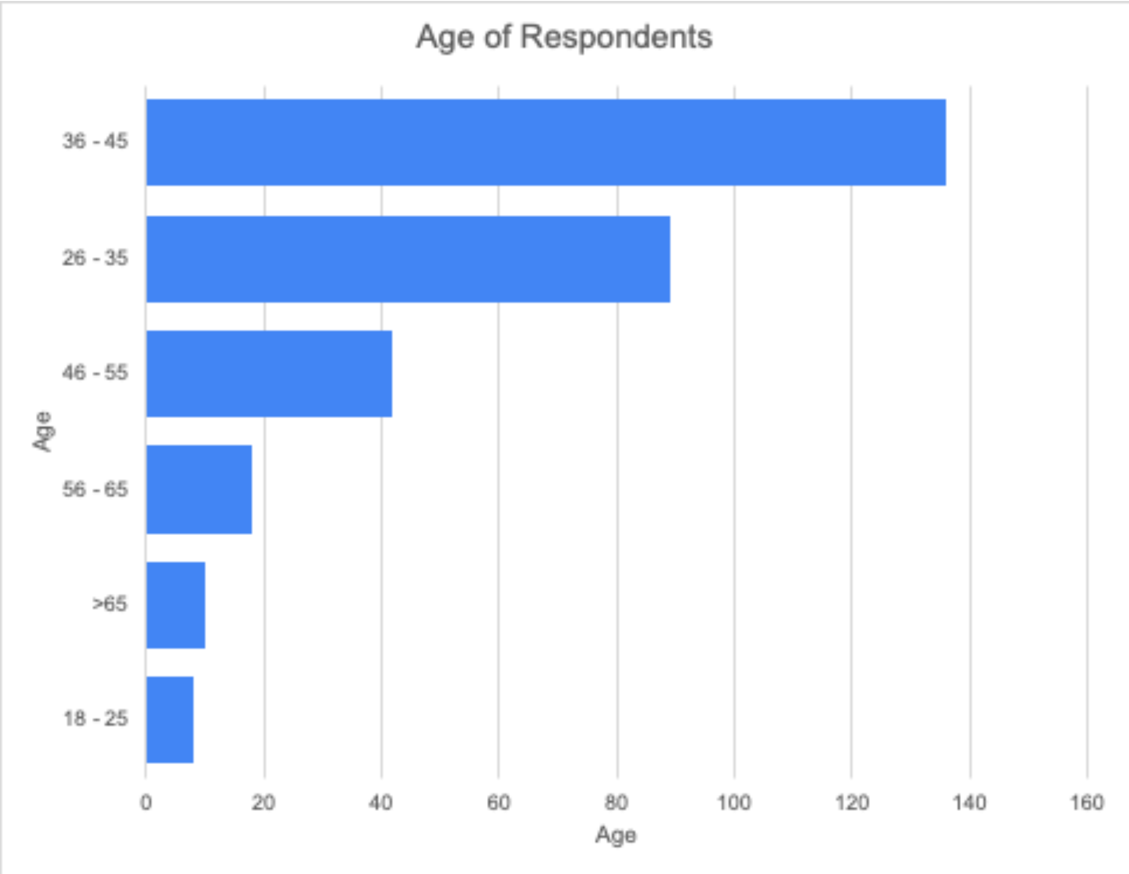


Figure 13. Age of Respondents

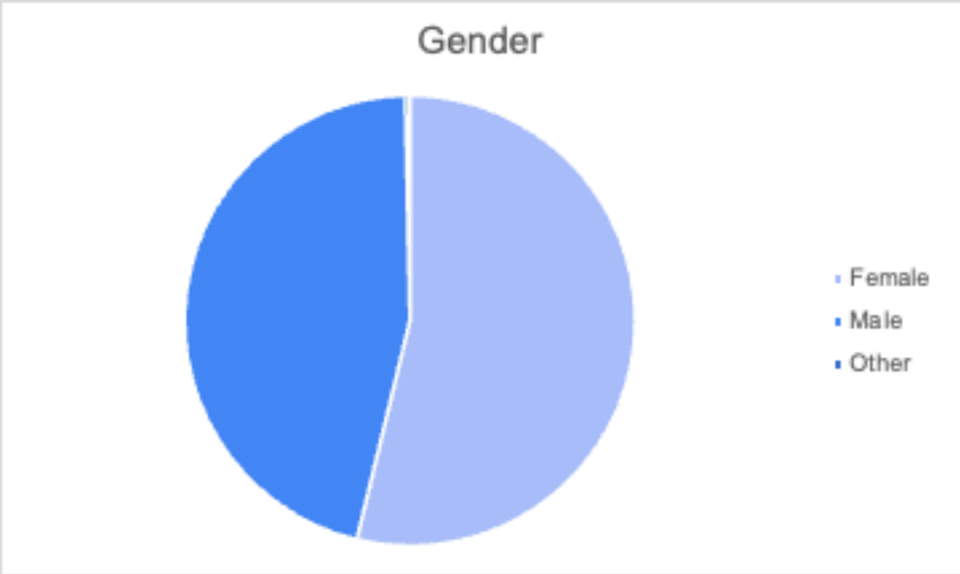


Figure 14. Gender Dispersion

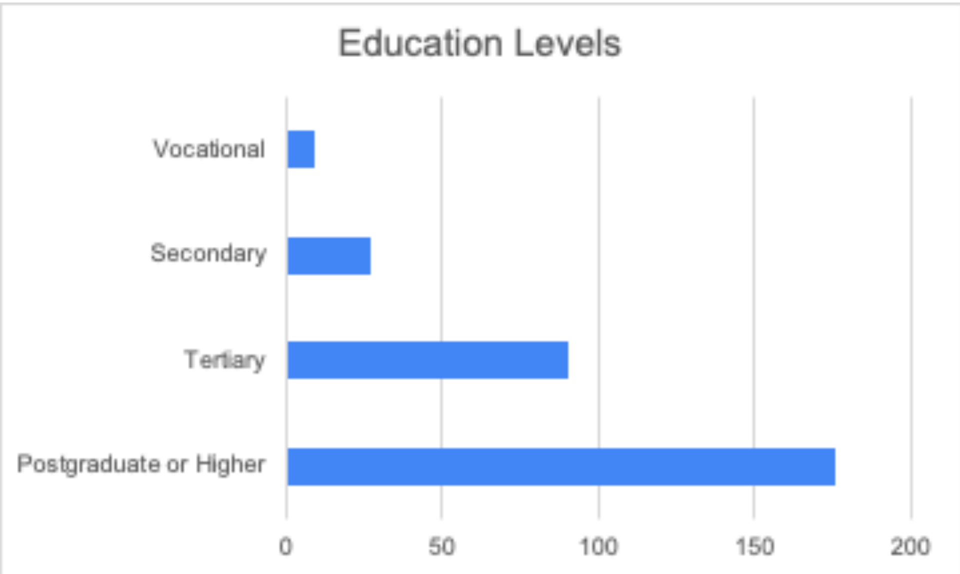


Figure 15. Education Levels of Respondents