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The behavioural intention to adopt Digital Financial Services in South Africa

Olwethu Vuyo Nkosi Bodlani

A research report submitted to the Faculty of Commerce, Law and Management, University of the Witwatersrand, in partial fulfilment of the requirements for the degree of Master of Management in the field of Digital Business

Johannesburg, 2023

ABSTRACT

South Africa has made significant progress towards expanding financial services by using digital technologies, with 81% of the population above sixteen years of age having formal bank accounts. Despite this significant increase, it still remains a cash-dependent country. The owners of these bank accounts use them as mailboxes, with 40% found dormant for low-income households. This phenomenon indicates that the adoption of the Digital Financial Services (DFS) tools (bank cards) is low. Social grant recipients are found to follow this trend, with 58% using their accounts as mailboxes, while 2% are considered dormant.

This study set forth to examine a set of factors (enablers and inhibitors) that were likely to predict DFS tool adoption intention behaviour, using the Unified Theory of Use and Acceptance of Technology (UTAUT), Technology Readiness Index, and the Resistance Theory of Innovation to underpin a conceptual model comprising seven “facilitators” and three “barriers” as identified potential determinants.

Quantitative analysis methods were used to test the conceptual model by surveying social grant recipients (n = 215) from the King Sabata Dalindyebo (KSD) Local Municipality in South Africa’s Eastern Cape Province. Findings showed that five enabling factors, namely performance expectancy, effort expectancy, perceived value, price benefit, and trust, were significant predictors of behavioural intention to adopt DFS. Contrary to observations from the existing literature on DFS adoption, all three inhibiting factors, namely perceived cost, unavailability of facilitating conditions and perceived risk, were not found to be significant predictors of behavioural intention to adopt DFS.

The study found that among study participants, facilitating factors significantly influenced behavioural intention to adopt DFS barring facilitating conditions and network externalities. The barriers were all found not to have any significant effect on the behavioural intention to adopt DFS. These findings aligned with existing literature on DFS and “fintech” adoption in emerging economies. The study also highlighted the importance of trust and communication between service providers and consumers to drive DFS adoption in South Africa.

KEYWORDS

Digital Financial Services (DFS), Social Grant, Unified Theory of Acceptance and Use of Technologies (UTAUT), Technology Readiness Index (TRI), Resistance Theory of Innovation, Behavioural Intention to Adopt, Fintech, South Africa

DECLARATION

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

Name: Olwethu Vuyo Nkosi Bodlani Signature: OVN Bodlani

Signed at …Johannesburg…….

On the …12th day of May 2023…..

DEDICATION

To all the dreamers who are fighting each day for their dreams…

ACKNOWLEDGEMENTS

I want to acknowledge everyone who contributed to and encouraged me throughout my studies. To my parents, Nelisa and Mlamli Bodlani, I appreciate you for supporting me with this endeavour. I would particularly like to thank my supervisor, Dr Maradona Gatara, for taking this journey with me. I have learned much from you and will always treasure the times you pushed me beyond my comfort zone and the support you showed me through this journey.

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LIST OF ACRONYMS

Acronyms	Description
AI	Artificial Intelligence
AVE	Average Variance Extracted
BI	Behavioural Intention
DFS	Digital Financial Services
DSD	Department of Social Development
EE	Effort Expectancy
EFA	Exploratory Factor Analysis
FC	Facilitating Conditions
Fintech	Financial Technology
ICASA	Independent Communications Authority of South Africa
ICTs	Information and Communication Technologies
IPMA	Importance-Performance Map Analysis
KSD	King Sabata Dalindyebo
LSM	Living Standards Measure

NE	Network Externalities
NPS	National Payment System
PASA	Payments Association of South Africa
PB	Price Benefit
PC	Perceived Cost
PCA	Principal Component Analysis
PCFA	Principal Component Factor Analysis
PE	Performance Expectancy
PLS-SEM	Partial Least Squares – Structural Equation Modelling
PR	Perceived Risk
PV	Perceived Value
SACU	South African Customs Union
SARB	South African Reserve Bank
SASSA	South African Social Security Agency
SDG	Sustainability Development Goals
SI	Social Influence

SPSS	Statistical Package for the Social Sciences
T	Trust
TAM	Technology Acceptance Model
TPB	Theory of Planned Behaviour
TRI	Technology Readiness Index
UFC	Unavailability of Facilitating Conditions
UTAUT	Unified Theory of Acceptance and Use of Technology

CHAPTER 1. INTRODUCTION

1.1 Statement of purpose

The purpose of this study is to examine the effects of a set of determinants on behavioural intention to adopt digital financial services in the context of South Africa.

1.2 Background of the study

Digital Financial Services (DFS) is defined as leveraging Information and Communication Technologies (ICTs) for cost-efficient delivery channels (David-West, 2016). DFS includes electronic payment systems and mobile phone-enabled solutions incorporating mobile financial services.

Financial Services have, over time, become digitised. The history of digitising financial services started with banking in 1953 when the Stanford Research Institute built the first bank mainframe for the Bank of America (Retail Banker International, 2020). Over time, significant improvements have been introduced, starting with the magnetic strip on cards enabling customer transactions via a swiping mechanism in the 1970s. Subsequently, bank cards with embedded microchips were pioneered in the 1980s (Haridass, 2020), followed by the introduction of mobile solutions in the late 1990s. The first patent for mobile payment systems (Hui et al., 2002) was filed at the turn of the millennium.

Low marginal costs characterise DFS and introduce transparency in the financial system (Museba et al., 2021; Pazarbasioglu et al., 2020). As such, organisations can offer customised products at more affordable rates. This has been observed by the introduction and success of less regulated, technology-enabled non-banks into the financial system (International Finance Corporation, 2017). Due to their low marginal costs, these non-banks have offered products cheaper than existing institutions burdened with infrastructure and regulations (International Finance Corporation, 2017).

Electronic payment system adoption and the factors that determine it are essential to understanding the uptake of DFS. ICT adoption by banks has created a fertile ground for building electronic payment systems provided as service offerings to customers (Oyelami et al., 2020). Electronic digital platforms are, however, not the only form of DFS. Mobile money platform solutions are included as DFS and provide access to financial services through mobile phones (Chibba, 2009).

In countries such as Uganda, where factors influencing the adoption of digital financial services, financial technologies (fintechs), and mobile money have been closely studied, it has been observed that building awareness, customer education, value proposition, and product availability through an agent network are some of the critical ingredients that result in adoption (Museba et al., 2021). Moreover, when these factors are considered, an increase in mobile money services and digital financial services can be observed, particularly in rural communities (Museba et al., 2021). This, therefore, can potentially lead to financial inclusion.

According to Machasio (2020), access to mobile money accounts rose from 34% in 2011 to 43% in 2017, while the percentage of consumers doubled between 2014 and 2017. This indicates an uptake in DFS in Africa as it allows users to access digital payments. Countries in this region registered more mobile accounts than traditional bank accounts. However, this still has not addressed the financial exclusion seen in Africa (Machasio, 2020). The COVID-19 pandemic has encouraged government officials and health practitioners to advocate using cashless services to limit its spread (Machasio, 2020). This push can assist in driving DFS as banks and Fintechs in Africa were instrumental in lowering barriers to adoption. This trend has been observed in countries such as Uganda (Museba et al., 2021).

Considering the pandemic, banks and Fintechs in Uganda have zero-rated person-to-person, wallet-to-bank, and bank-to-wallet transactions (Agur et al., 2020; Museba et al., 2021). As such, DFS solutions were not expensive to customers, and greater access was provided to low-income earners. Similarly, the government raised the electronic payment limit in Egypt to encourage digital

payments (de Girancourt et al., 2020). With these recent developments in DFS adoption, the question of whether changes made to adapt to the COVID-19 global pandemic will have a lasting impact remains unanswered. This raises questions on whether the revisions completed in light of the pandemic will play a significant role in ongoing DFS adoption.

According to the 2022 State of the Industry report on Mobile Money published by the GSMA, Sub-Saharan Africa saw 17%, 12%, 23%, and 40% increases in Mobile Money registered accounts, active accounts, transaction volume, and transaction value (US$) respectively, in 2021, from the equivalent rates of 12%, 18%, 15%, and 26% reported the previous year (GSMA, 2021). The increased mobile money services between 2020 and 2021 indicate that creating such incentives can drive DFS adoption.

1.3 Context of the Study

According to the position paper on Electric Money published by the South African Reserve Bank (SARB), only registered banks may issue electronic money (van Niekerk & Phaladi, 2021). Thus, any non-banking company would have to partner with a registered bank in South Africa to transact via electronic payments and issue money. This raises the question of whether the need to partner with a registered bank inhibits or enables DFS adoption. According to Financial Sector Conduct Authority (2022) 81% of South Africa's population in 2021 (above 16 years) had a formal bank account, yet its citizens are still cash dependent. Moreover, informal merchants hesitate to transact using cash (Soutter et al., 2019). Notably, mobile money payment platforms have not gained sufficient momentum in South Africa compared to countries such as Kenya. This was evidenced by the discontinuation of DFS products like M-Pesa and MTN Mobile Money in 2016 (Soutter et al., 2019). Even with its highly banked citizens, access to mobile technology, and the existence of banks and non-bank companies providing DFS through mobile technology, South Africa had a high mobile penetration rate as of 2016 (Soutter et al., 2019).

Introducing new South African banks such as Tyme Bank and Discovery Bank does not necessarily mean new customers have been included in the Banking sector. According to the Financial Sector Outlook Study, large bank customers have decreased. At the same time, the number of new banks has increased. For instance, many customers banking with Tyme Bank, a new bank were previous account holders from other banks and not new to the banking industry (Financial Sector Conduct Authority & Genesis Analytics, 2022). Introducing new banks does not mean new customer adoption but rather migration from an existing bank.

In 2017, SASSA introduced bank accounts for recipients with the aim of introducing the digital distribution of grants. This has resulted in South Africa having a bank account adoption rate of 81% in 2021. Moreover, if the Grant Holders are removed, South Africa's bank adoption rate stands at 69% representing the formally banked (Financial Sector Conduct Authority & Genesis Analytics, 2022). According to an article by Finmark Trust (2020) based on FinScope data collected in 2019, 87% of South Africans use cash, 35% use some form of digital payment, and 0.1 use mobile payment (Finmark Trust, 2020). This evidences that although South Africa has the capacity for and customers to access digital payment solutions, its citizens are not adopting these platforms.

South African banks offer mobile wallet products, with FNB, ABSA, and Standard Bank offering the "eWallet", "CashSend", and "Instant Money" platforms, respectively. These wallet services in South Africa require one of the parties involved in the transaction to have a bank account. The "WeChat Wallet" was introduced in 2013 by Chinese multinational technology company Tencent as an application allowing customers to manage their payments using mobile devices (Matemba & Li, 2018). Later, the instant messaging, social media and mobile payment application WeChat, developed by Tencent, partnered with Standard Bank in South Africa to provide its functionality (Vermeulen, 2020). However, in 2020, it was announced that "WeChat Wallet" services would be shut down at the end of June that year (Vermeulen, 2020).

1.4 Research problem

South Africa is a cash-based economy despite most of its population having access to a formal bank account (Financial Sector Conduct Authority & Genesis Analytics, 2022). According to the Pew Research Centre, 8% of South African adults shared a mobile device and did not have it, with 5% of the population not having access to it as of 2018 (Silver et al., 2019). According to the 2020 State of ICT Sector report, 91% of citizens in South Africa were found to have smartphones as of 2019 (ICASA, 2020).

As such, South African citizens can access digital platforms to use DFS. However, cash is still the predominant mode of transaction in South Africa. There is a lack of knowledge of what factors would inhibit or enable DFS adoption among consumers in South Africa. Therefore, this study adds to the body of knowledge and addresses this identified gap regarding the lack of adoption of DFS in South Africa and what factors will influence its use at the individual-level.

The COVID-19 global pandemic impacted the use of DFS by pushing cashless payments and decreasing the spread of the disease by exchanging physical cash (McKenzie, 2020, as cited in Museba et al., 2021). GSMA (2021) indicated that the increasing need for cashless transactions was crucial in increasing mobile money use across Sub-Saharan Africa. Although mobile money subscriptions in Sub-Saharan Africa increased, the Southern Africa region had the highest increase in Africa, with a 28% increase from 2019 in active mobile accounts. The total number was still low at 3 million active accounts compared to other regions like West Africa at 47 million and East Africa at 94 million, respectively (GSMA, 2021).

1.5 Research questions

To address the emergent problem identified, the following research questions are formulated for the study:

1. What inhibiting and enabling factors are suggested in the existing literature as the most likely to influence individual-level adoption and usage of DFS among South African consumers?
2. What are the effects of this inhibiting and enabling individual-level factors on South African grant recipients'' adoption and usage of DFS?

1.6 Objective of the Study

To answer the formulated research questions, the following study objectives are specified:

1. Identify inhibiting and enabling individual-level consumer DFS adoption and usage constructs (factors) from the existing literature.
2. Develop and empirically test a conceptual model of the relationships between the identified constructs (factors) and relative effects on individual-level consumer DFS adoption and usage.

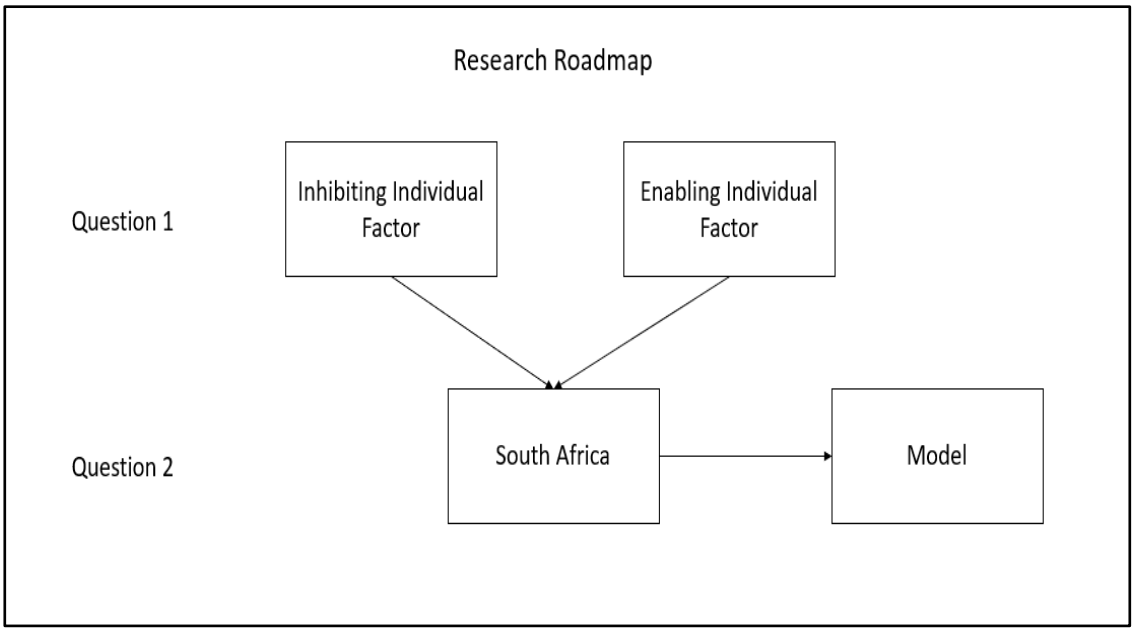

Figure 1: Research Roadmap

1.7 Rationale

This study focuses on the adoption of DFS in South Africa by users with access to digital technologies. This analysis is essential because DFS can facilitate the

provision of services to the underprivileged through digital and electronic money platforms (David-West et al., 2018). According to the Gates Foundation's "Fighting Poverty through Payments" (2013) report, the adoption and use of digital payments can simplify the financial lives of the financially disadvantaged (Voorhies et al., 2013). In South Africa, more than half of its citizens live below the poverty line, with an estimated 55% (30.3 million people) (Department of Social Development, 2021; World Bank, 2020). DFS is one way in which this poverty can be addressed. Furthermore, DFS will be essential in the context of South Africa. Thus, South Africa has an environment in which DFS can flourish. There is high access to mobile devices and formal bank accounts, and the need for DFS is prevalent. Even though there is a readiness for DFS usage, South Africans are not adopting it at the rate of other countries in Sub-Saharan Africa. This lack of adoption and usage is a phenomenon that warrants further investigation. The present study examines what determining factors would cause South Africans to adopt and use DFS technologies given access to these platforms. The study will also be helpful to government agencies and policymakers in ensuring that policies for financial inclusion are made while considering key determining factors that can inhibit or enable DFS adoption and usage.

The study constitutes several contributions, described as academic, practical, and global:

1.7.1 *Academic Contribution*

The study signifies a theoretical and methodological academic contribution to the DFS adoption and usage literature by focusing on factors that inhibit and enable adoption and usage in the context of South Africa, thereby filling a knowledge gap. Although a significant amount of research has been conducted on DFS adoption, the present study provides the unique contextual perspective of South Africa and its social grant recipients. The study could not identify a substantive body of academic research and empirical evidence on this specific group from the existing literature. Thus, an additional dimension to research on DFS adoption was provided through the present study.

The study further contributes by expanding the UTAUT and UTAUT 2 models to include elements from the Technology Readiness Index (TRI) and Resistance Theory of New Innovation. Empirical testing of an enhanced model test revealed that the factors identified as facilitators directly affected behavioural intention to adopt DFS in the South African context. In addition, the existing literature was drawn on to develop a theoretically underpinned conceptual model for the empirical testing of hypothesised effects on DFS adoption behaviours using cross-sectional survey design and multivariate data analysis techniques.

1.7.2 *Practical Contribution*

The present study will benefit Fintechs, banks, and any institution that introduces digital payments services in South Africa, thereby signifying a practical contribution. Specifically, the study assists these stakeholders by identifying key determining factors that can inhibit and enable the adoption and usage of DFS to understand the South African environment and help providers successfully implement these technologies. The study also assists the government with policymaking for Financial Inclusion and the uptake of DFS from an evidence-based perspective. The factors identified and their relationship with adoption behaviours will provide the necessary impetus to drive DFS uptake, thereby supporting South Africa's Fintech and banking industries.

1.7.3 *Global Contributions*

Through the intended academic and practical contributions made, the present study signifies the application of global best practices to addressing the DFS adoption phenomenon in a South African setting. Specifically, as part of the broader African context, the rigorous development of a conceptual model to guide the study and that is replicable to other developing countries where the environment is similar to that of South Africa, will likely foster an improved understanding of DFS adoption at the individual-level. Therefore, an emergent global contribution was made through the study.

1.8 Delimitations of the study

The focus of the present study is DFS payment platforms for consumers. The study will not focus on the other types of DFS that Fintechs and banks can offer, such as digital lending and digital remittances (Agur et al., 2020). The study will focus on South African Social Security Agency (SASSA) social grant recipients who only use traditional cash-based payment mechanisms or use their bank (card) accounts as post boxes. They receive money through it but then use the cash to transact and interact with suppliers.

1.9 Definition of terms

Digital Financial Services (DFS) is defined as leveraging Information and Communication Technologies (ICTs) for cost-efficient delivery channels (David-West, 2016).

Schueffel (2016) conducted empirical research and defined *Financial Technology (Fintech)* as a new financial industry that uses technology to improve financial activities.

Behavioural Intention (BI) is defined through the Theory of Planned Behaviour (TBP) as the individual's probability of engaging in a specific behaviour which is of interest and thus can be seen as the immediate predecessor of an actual behaviour (Arora et al., 2017).

"*Technology Adoption* is the choice to acquire and use a new innovation" (Gao & Krogstie, 2016). Therefore, in this study, technology adoption is the consumer's choice to acquire and use DFS in the context of South Africa.

1.10 Assumptions

The following assumptions will be considered for this study:

- Social grant recipients in South Africa have a SASSA bank account (DFS tool) which they can use to access their social grants.

- Despite having access to a DFS tool, the typical consumer uses traditional cash-based payment mechanisms for goods or services.

1.11 Chapter Outline

Chapter 1: Introduction

This chapter introduces the history and background of the context of the study, its purpose, research problem, research questions and objectives, the significance of the study, delimitations, assumptions, and the definition of terms used by the researcher.

Chapter 2: Literature Review

This chapter is divided into three sections. The first section provides the theoretical background of the study. The second section focuses on the theoretical underpinnings for particularly technology adoption intention behaviour examined in the study. The last section develops an empirically testable conceptual model that will be examined to understand DFS adoption in South Africa.

Chapter 3: Research Methodology

This chapter covers the research design and methodological approaches used in the present study. It also delineates the methods used for collecting and analysing the data while describing the study's target population and sample size. The chapter is concluded with a discussion of ethical considerations.

Chapter 4: Analysis and Presentation of Results

This chapter details the steps and processes taken to analyse the responses received from the respondents surveyed. The chapter then presents the findings of the empirical analyses undertaken for this study.

Chapter 5: Discussion of Results

This chapter presents a discussion of previous chapters' results obtained following tests (empirical analyses) of hypothesised conceptual model relationships as presented in Chapter 4, in relation to the literature review or previous works related to the concept of DFS and technology adoption intention behaviours explored in Chapter 2.

Chapter 6: Conclusion and Recommendations

This chapter summarises the study by discussing contributions to research and practice. Recommendations to academics and practitioners concerned with the adoption of DFS, particularly in the context of South Africa, but also useful for other similar emerging contexts internationally, are also presented.

CHAPTER 2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1 Introduction

In this chapter, the existing literature will be evaluated to understand factors that inhibit and enable Digital Financial Service (DFS) adoption in South Africa. The initial sections will provide a background to DFS before providing a global view of the phenomenon by investigating trends that have been observed globally. This will allow the researcher to contextualise DFS and its adoption in a Sub-Saharan African context. The context of South Africa will be introduced, and background information on the country provided, after which nationwide DFS trends will be explored and highlighted. Thereafter, the state of the payment system in the South African context will be unpacked, and the researcher will seek to understand the potential adoption of DFS in South Africa and its impact on financial inclusion in the country. Lastly, this chapter will use existing theories to underpin the development of a conceptual model used to examine and explain the effects of factors that can influence (inhibit or enable) behavioural intention to adopt DFS in the aforementioned context.

2.2 The Concept of Digital Financial Services (DFS)

2.2.1 *Origins and History of Digital Financial Services (DFS)*

The concept of cashless service has existed since the 1950s, with key initiatives to move users from using cash-based to non-cash-based services (Haridass, 2020). This allowed consumers to pay for goods without having to use cash as a transaction medium. Significant changes were made in DFS in the 1950s with the introduction of the first mainframe for the Bank of America (Haridass, 2020; Retail Banker International, 2020), and the concept of a charge card by Diners Club which would then become the credit card (Rosenberg, 2020). Subsequently, in the 1960s, Barclays UK launched the first debit card (Retail Banker International, 2020).

The advancement during this period allowed for bank cards with embedded microchips and in the UK, the introduction of a direct bank by Midland Bank using call centres in the 1980s (Haridass, 2020; Retail Banker International, 2020). The introduction of the Internet in the 1980s allowed for the opening of electronic payment terminals (Haridass, 2020). These terminals introduced speed point machines that enabled consumers to pay using their chip-enabled cards when transacting. According to CSG Forte (2021), online banking services were introduced to consumers in the 1990s due to the Internet's emergence (CSG Forte, 2021).

During the late 1990s, with the move to Web 2.0, significant improvements were made to the Internet and related banking services (CSG Forte, 2021). According to UBU International, a company which offers businesses an opportunity to be part of an online marketplace, "in 1994, Stanford Federal Credit union is credited as the first organisation to offer their clients an online payment system." Due to the above interest in Digital Payments, many digital payment giants and e-commerce organisations were launched. Examples include Amazon in 1994, Millicent in 1995, Ecash in 1996, and PayPal in 1998 (CSG Forte, 2021; UBU International, 2022).

During the late 1990s, technology allowed consumers access to mobile web payment (WAP) (Rampton, 2016). In the 2000s, the first Mobile Payment Solution patent was issued in America, beginning the move to mobile payments in the digital payments journey (Hui et al., 2002). In the late 2000s, Apple and Android operating systems were released, and Bitcoin was invented (Rampton, 2016). These technology interventions allowed for the introduction of Google Wallet in 2011, Apple Pay in 2014, and Samsung Pay in 2015 (Rampton, 2016). These mobile wallet solutions allowed Smartphone users to use their mobile devices to conduct payments.

According to Koponen (2006), online payment systems can be broadly classified into account-based and electronic currency systems (Bezhovski, 2016). The account-based system requires the users to have a bank account, and payments will be made through it. In addition, the Electronic Currency system requires the consumer to have electric currency to pay (Bezhovski, 2016).

2.2.2 *Global Trends in Digital Financial Services (DFS)*

During the pandemic, there has been an increase in the use of digital platforms in South Africa (World Bank, 2021). Specifically, according to IMF research in light of the COVID-19 pandemic, DFS has been spotlighted to curb its spread by allowing for social distancing and government disbursement (Agur et al., 2020; GSMA, 2021). This spotlight has resulted in DFS being used to respond to COVID-19 shocks. DFS, in terms of payments, comprises digital commerce and Mobile POS (m-POS). These digital payment methods saw an increase in adoption from 2017 to 2019 (Agur et al., 2020).

Mobile Money or m-POS are transactions processed using mobile channels and wallets (Agur et al., 2020). Agur et al. (2020) observed that in 2019, over a billion users conducted mobile POS payments, and in 2020, there were a registered 1.2 billion customers with 300 million accounts active globally (GSMA, 2021). Registered mobile accounts increased by 13% from the previous year, and active accounts increased by 17% globally (GSMA, 2021). Mobile Money providers were critical in the national response to COVID-19, providing a path to financial assistance quickly, safely, and efficiently (GSMA, 2021).

Figure 2 below illustrates the net additions to registered mobile accounts per region. Sub-Saharan Africa was the most considerable growth region, with 43%. East Asia and the Pacific recorded the second-highest growth with 34% net addition. Further, it was noted that in South East Asia, more than half the services in this region have more than one million registered accounts (GSMA, 2021). South Asia's 11% increase resulted in 305 million registered accounts. South Asia is second after Sub-Saharan Africa in total registered mobile accounts (GSMA, 2021). The Middle East and North Africa, Latin America, the Caribbean, Europe, and Central Asia had 3%, 8%, and 1% increases during 2020 (GSMA, 2021), respectively. The growth in Latin America and the Caribbean was due to the government providing relief funds via mobile money during the pandemic (GSMA, 2021).

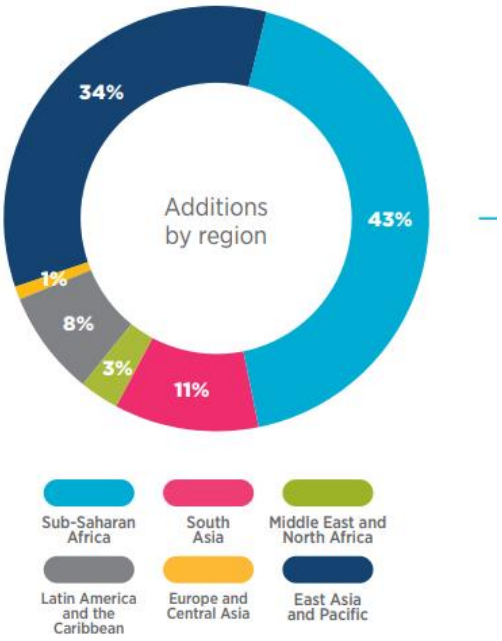

Figure 2: Net Additions to Registered Accounts (GSMA, 2021)

Another new DFS product which has seen tremendous uptake due to COVID-19 is Digital Wallets. According to Barackath & Banu (2021), “digital wallets are monetary accounts that enable clients to hold money, carry out transfers, and monitor disbursements from electronic devices. Digital wallets are also interfaces for using cryptocurrencies (Barackath & Banu, 2021) and digital wallets, unlike mobile wallets.

2.2.3 *Digital Financial Services (DFS) in Sub-Saharan Africa*

Digital Payments have been on the rise in Africa, particularly mobile money, for which there were 161 million active customers in 2020, an 18% increase compared to the previous year (GSMA, 2021). Sub-Saharan Africa saw tremendous growth with 43% net additions of a registered account. The development has resulted in Sub-Saharan Africa having the most active customers with 159 million users and thus leading globally in terms of mobile money adoption and usage. Mobile Money in Sub-Saharan Africa drives financial inclusion (Agur et al., 2020; Soutter et al., 2019).

Approximately 60% of adults in Sub-Saharan Africa cannot access formal financial services. Thus, cash is the predominant medium of exchange (Soutter

et al., 2019). The pandemic escalated the need for DFS as it could allow for social distancing, enable governments to disburse funds to the needy, and allow households and firms to access online payments rapidly (Agur et al., 2020). The need for DFS due to COVID-19 and the high adoption rate of mobile technology in Sub-Saharan Africa created the perfect environment for the uptake of mobile money, as explained by Museba et al. (2021). In their study, they found that the adoption of mobile money and DFS is driven by mobile device penetration coupled with the need to access financial products and services for the unbanked (Museba et al., 2021).

East Africa has led the adoption of mobile money, with 94 million of the 161 million active customers coming from East Africa (GSMA, 2021). During the pandemic, countries in East Africa have been leveraging mobile money platforms like M-Pesa to conduct transfers between unbanked households and the informal sector (Agur et al., 2020). To assist in the digital adoption of services, some of these countries were seen implementing policy changes to increase adoption. Uganda cut mobile money transfer fees to zero (Agur et al., 2020; Museba et al., 2021). Similarly, Kenya and Mozambique cut mobile money transfer fees to zero and raised transaction limits (Agur et al., 2020). These policy changes have assisted in driving the adoption of DFS solutions since the COVID-19 pandemic.

In 2019, a study by the IMF found that in Eastern and Western Africa, the main driver of financial inclusion is mobile money (Ebong & George, 2021). Hence, it is essential to understand this region's payment adoption trends. According to Ebong & George (2021), the main driver of financial inclusion in Uganda has also been mobile money.

2.3 Digital Financial Services (DFS) in the Context of South Africa

2.3.1 *A Profile of South Africa*

a. *Overview of South Africa*

South Africa is a country found in the Southernmost region of Africa, with approximately 60 million people in 2021 (O'Neil, 2022; Statistics South Africa, 2021). South Africa is a diverse nation with a reasonably new democracy of 28 years old, since its establishment in 1994. The ruling party African National Congress (ANC) has been in power since 1994 and drives South Africa's policy agenda (World Bank, 2022b). The South African government has promoted social development changes and made progress in reducing poverty since 1994 (United Nations, 2020; World Bank, 2020). In 2011, some of the progress made to erode poverty reversed and thus caused its rate increase to approximately 50% (World Bank, 2020).

According to the United Nations (2020) Common Country Analysis report, "the South African government has been accused of embracing policies which are not far-reaching enough to address the high unemployment, poor service delivery, and inequalities between the rich and poor". This corruption has also hampered the country's progress in achieving its Sustainable Development Goals (SDGs), which includes poverty (SDG1) (United Nations, 2020). Therefore, the reversal of the progress in addressing poverty in South Africa can be attributed to corruption in which the South African government is believed to be embroiled.

b. *Historical Background*

Poverty and inequality in South Africa can be traced back to its Apartheid period (Rousseau, 2019). In 1993, just before South Africa's first democratic election, South Africa scored a Gini coefficient of 0.593, classifying it as one of the most unequal countries in the world (Rousseau, 2019). Apartheid was a system of racial segregation in South Africa, which the pre-1994 South African government enforced through various Acts and policies. Although this system ended in 1994,

the divides perpetuating poverty in South Africa are still entrenched and felt today (United Nations, 2020). South Africa, in its 28 years of democracy, has on a few occasions been identified as being among one of the most unequal countries in the world by the World Bank, with the last report being released in 2022 (The World Bank, 2022) since the first published in 1994 (Rousseau, 2019).

South Africa's inequality and poverty have seen the country experience ad-hoc incidents of xenophobic crimes and looting. These incidences have involved looting of African foreign-owned businesses in South Africa (United Nations, 2020). These attacks negatively impact the South African government's efforts to attract and promote investment in the country (United Nations, 2020). Despite the above and South Africa's apartheid history, South Africa has a sophisticated and large financial sector, as South African banks dominate the financial industry in the Southern Africa Customs Union (SACU) (World Bank, 2022a).

c. *Geographical Background*

The geographical background that informs the context of the present study will be examined in terms of two definitions. The first is based on where South Africa the country is located. The second will unpack the impact of location on its citizenry and its effects on equality and poverty.

Figure 3 shows South Africa situated at the Southern tip of Africa. South Africa has a long coastline which stretches more than 2000 km (Department of Government Communication and Information System, 2016). The coastline starts from the border with Namibia going all the way across the west of South Africa, down to the South and East, to the Mozambique border. With its location at the tip of Africa, South Africa is isolated from its major trading partners like Europe, Eastern Asia, and North America. This isolation helped reinforce the system of apartheid (Mabin et al., 2022).

Geography is essential as it is a crucial determinant of access to opportunities (World Bank, 2022a). Like other countries in the SACU, South Africa has a long history of spatial segregation due to the Apartheid regime's racially motivated policies (World Bank, 2022a). These policies resulted in black South Africans settling in rural communities and their white counterparts in urban settlements.

However, many factors contribute to earning inequality. The inequality in Southern Africa indicates that geography (location) contributes to access to opportunities.



Figure 3: Political Map of South Africa (Nations Online Project, 2023) (https://www.nationsonline.org)

d. *Economic Background*

Despite the inequality, apartheid regime and poverty, South Africa has a sophisticated financial sector with its asset to GDP ratio above most emerging markets at 129% of the domestic credit to the private sector (Financial Sector Conduct Authority & Genesis Analytics, 2022). According to the United Nations Common Country Analysis Report, South Africa is Africa's most diversified and financially integrated economy (United Nations, 2020). The country's strong financial sector has been attributed to the South African banks' dominance of the financial industries in other SACU countries.

Although South Africa has a robust financial sector, this has not insulated the South African economy from the shocks of COVID-19. The pandemic widened

the inequality gap in South Africa by contributing to severe and unequal job losses, as low-wage workers suffered four times more than their high-wage counterparts (World Bank, 2021). COVID-19 has resulted in the deepest recession since Apartheid, with South Africa's GDP shrinking by 7% in 2020, the fiscal deficit growing to 12.9%, and the public debt to 78.8% of the GDP (World Bank, 2021). These changes have negatively impacted South Africa's economy as South Africa faces a high debt cost.

A high debt cost means that South Africa is limited in terms of development spending and public investment, needed to address inequality. Advanced economies, although they were also impacted by COVID-19, unlike South Africa and other emergent economies, can service their debt at a low-interest cost. Thus, for an advanced economy, a high debt cost is not as severe as it is for emergent economies (The World Bank, 2021). In 2021, global market conditions improved, which allowed South Africa to benefit. However, due to high financing requirements, South Africa remains vulnerable (World Bank, 2021).

e. *Demographic Background*

South Africa's demographic trendline is increasing (Figure 3), as many working adults live longer and are healthier than the previous generation (World Bank, 2021). The observed increase means South Africa can use the rise in the adult workforce to address development opportunities and leverage this. Moreover, its youth must be integrated into the workforce. Figure 4 details the unemployment rate in South Africa using both strict and expanded definitions.

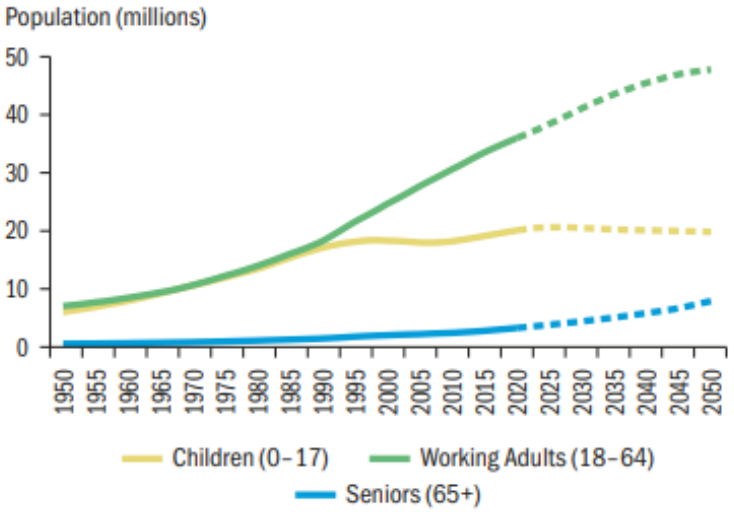

Figure 4: South Africa's Demographic Opportunity (World Bank, 2021)

The unemployment rate is at 74% (expanded definition) for the age group between 15 - 24 years, and this large percentage adds to the country's poverty. The pandemic increased the unemployment rate where in the second quarter of 2022, 2.2 million jobs were lost in South Africa (The World Bank, 2021). This COVID-19 shock resulted in a 13.6% decrease in overall employment in South Africa. While the South African population is living longer, with South Africa's Demographic Momentum shift, but the country is experiencing high unemployment due to a limited job market (World Bank, 2021). Demographic Momentum is observed when the population apparently continues to grow despite a decline in fertility because of its young age distribution (Schoen, 2006). This current phenomenon does not add to improving the economy as it increases unemployment (World Bank, 2021).

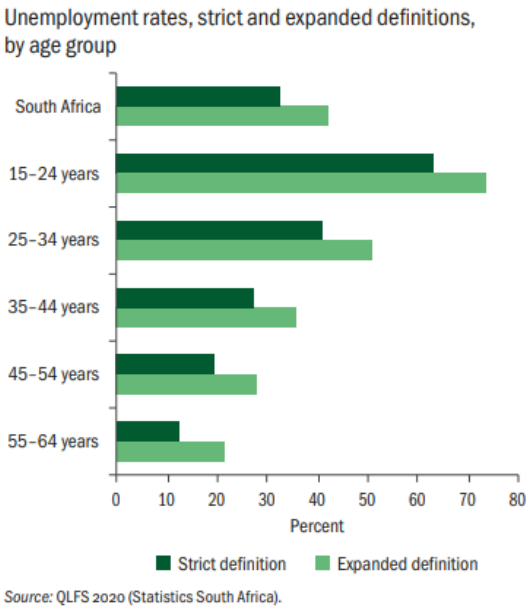

Figure 5: South Africa's Unemployment Stats for 2020 (World Bank, 2021)

Table 1 presents a summary of key facts and figures.

Table 1: South Africa Facts and Figures	
General Profile	
Official Name	Republic of South Africa
Capital City	Tshwane (administrative) Cape Town (legislation) Bloemfontein (Judicial)
Other Cities	Johannesburg, eThekwini, Gqeberha, Nelspruit, Polokwane, and Mthatha
Government	Republic. South Africa is a constitutional democracy with a three-tier system of government, a legislature, an executive, and an independent judiciary.
Geography	

Location	Southern Africa, at the southern tip of the African continent
Area	1 221 037 square kilometers
Terrain	Plateaus, savanna, desert, mountains, and coastal planes
Climate	Moderate, mostly semi-arid, and sub-tropical along the East Coast. Summers lasts from December to February, and Winters from June to August.
Natural Resources	South Africa is rich with natural resources such as Gold, Chromium, Antimony, Coal, Iron ore, Manganese, Nickel, Phosphates, Tin, Uranium, Diamonds, Platinum, Copper, Salt, Natural Gas, and Vanadium.
Demographics	
Nationality	South African
Population	2021: 60.1 million
Languages	Afrikaans, isiXhosa, isiZulu, isiNdebele, Sesotho, Setswana, siSwati, Tshivenda, Xitsonga, English, Sesotho sa Leboa, and Sign Language.
Unemployment	2022: 32.7%
Economy	
Industries	Mining, Automobile Assembly, Metalworking, Machinery, Textile, Iron and Steel, and Fertilizer.
Currency	The South African Rand (ZAR)
Gross Domestic Product (GDP)	-1.3%

Consumer Price Index	7.1%

Table 1: South Africa Facts and Figures (Nations Online Project, 2023; Statistics South Africa, 2023)

2.3.2 *Social Grants in South Africa*

South Africans are afforded social security and thus social grants through the South African constitution's Section 27(1)(c) (Garidzirai & Chikuruwo, 2020). Social Grants address South Africa's poverty and socio-economic challenges, which began before 1994 (Garidzirai & Chikuruwo, 2020). According to the Department of Social Development in South Africa, Social Grants are monetary payments of social assistance. The management, compensation, and administration of SASSA grants has been transferred to the South African Social Security Agency (SASSA) (Goldblatt, 2005), a statutory body of the Department of Social Development (DSD) in South Africa (Department of Social Development, 2022).

Social Grants in South Africa provide hope to citizens currently suffering from poverty and other socio-economic issues (Winchester et al., 2021). South Africa has various social grants created to assist multiple population segments. Social Grants in South Africa are available to all South African citizens, permanent residents, and refugees who meet the stated criteria for each grant (Department of Social Development, 2022). In this regard, the means test is where SASSA investigates the income and assets of the individual applying for the social grant to determine whether they qualify due to their monthly income being below a certain threshold (Western Cape Government, 2023). Table 2 details the various social assignments available in South Africa.

Social Grant	Description
Care Dependency Grant	Grant provided to parents or guardians of a child who is severely disabled and receives permanent care or support from parents or guardians who pass the means test.
Child Support Grant	Grant provided to parents or guardians of children in South Africa whose parents or guardians pass the means test.
Disability Grant	Grant provided to citizens, permanent residents, or refugees, who cannot work due to a medical condition or disability that pass the means test.
Foster Child Grant	Grant provided to the guardians of a child younger than 18 years who has been legally placed in their foster care by a court order.
Grant-In-Aid	The grant is provided to the recipient of the Older Persons, Disability Grant, or War Veteran's Grant, who requires full-time attendance by another due to their physical or mental disabilities.
Older Persons Grant	Grant is provided to citizens, permanent residents, or refugees older than 60 years and meets the means test.
Social Relief Grant	Social relief of distress is a temporary provision of assistance intended for persons in such dire material need that they cannot meet their own or families' most basic needs.
War Veterans Grant	The grant is provided to veterans who fought in the Second World War or the Korean War older than 59 years or disabled from the war who meet the means test.

Table 2: Social Grants Available in South Africa (Department of Social Development, 2022)

South Africa currently conducts a “Means Test” on the recipients of Social Grants to determine that the recipients meet the financial requirements required to receive a grant. Social Grants in South Africa are provided to recipients every month by using payment methods comprising cash payments at designated pay points like the Post Office and SASSA offices, deposited into a Bank Account including Post Bank (Department of Social Development, 2022). In South Africa, a recipient can obtain more than one Social Grant. Table 3 illustrates the number of recipients with more than one grant. Notably, as observed in 2021 a recipient can receive up to 5 social grants in South Africa (Parliamentary Budget Office, 2021).

Number of Social Grants a Recipient Has	Number of Recipients
1	8 951 474
2	2 059 866
3	420 839
4	24 656
5	170

Table 3: Number of Recipients per number of social grants (Parliamentary Budget Office, 2021)

According to the Social Grant Performance Report as of March 2021, the province which disbursed the most Social Grants is Kwa-Zulu Natal, with 2,446,537 recipients paid (Parliamentary Budget Office, 2021). This was followed by the next two provinces, Gauteng, and the Eastern Cape, with 1,911,013 and 1,709,751 recipients paid, respectively (Parliamentary Budget Office, 2021). Social Grants in South Africa are also rising, as the report shows an increase from March 2020 to March 2021 (Parliamentary Budget Office, 2021).

Child Support Grants contain the most significant number of recipients, as this grant was paid out to more than 12 million recipients from April 2020 to March

2021. This additional 12 million grants contributed to about 60% of the recipients that were paid, as the total per month for each period was approximately 18 million (Parliamentary Budget Office, 2021). The trend observed for Child Support Grants provided was that the number of recipients increased during this period (Parliamentary Budget Office, 2021).

2.3.3 *Trends in Digital Financial Services (DFS) in South Africa*

South Africa has made significant progress in banking sector penetration. In 2021, 81% of its population had a bank account (Financial Sector Conduct Authority & Genesis Analytics, 2022; Rodriguez et al., 2019). Despite the significant penetration, South Africa's weakened economy due to the pandemic has negatively impacted banks, with the essential banks reporting a decline in their profits in 2020 (Financial Sector Conduct Authority & Genesis Analytics, 2022).

According to a study by Accenture in South Africa, implementing vital digital initiatives in retail banking and insurance can unlock R1.2 trillion in value for businesses and society (Rodriguez et al., 2019). This potential was noted, and South Africa's financial industry saw the entry of "fintechs" and new digital banks. In 2019, South Africa introduced three digital banks (van Niekerk & Phaladi, 2021). Tyme Bank, one of the new digital banks, grew from 80000 customers in March 2019 to 250,000 the following month. This movement in South Africa's financial industry shows that South Africa has a small but fast-growing DFS industry through Fintech (Genesis Analytics, 2019).

A study conducted by Genesis Analytics (2019) in 2017 to determine the market size of "fintechs" in South Africa per segment indicated that the payment segment is the largest (with 68 active Fintech companies) and the most mature in South Africa. The study also found that many payment "fintechs" are registered as Third-Party Payment providers with PASA. One of the oldest Fintech payment platforms in South Africa, WiGroup in 2017 processed R1.8 billion in transactions (Genesis Analytics, 2019). Zoona, a South African-based Fintech operating in Zambia, Malawi, and Mozambique, processed $2 billion (about R27.9 billion) in transactions (Genesis Analytics, 2019). This contrast indicates that although

South Africa has a large Fintech industry, there is significant work in recruiting consumers to use these DFS platforms.

2.3.4 *Payment Systems in South Africa*

In South Africa, payment must go through South Africa's National Payment System (NPS). The National Payments Systems Act 78 of 1998 defines a payment system as "one that enables payment to be affected or facilitates the circulation of money and includes any instruments and procedures that relate to the system" (*National Payment Systems Act 78 of 1998*, 1998). Therefore, based on its definition in the Act, the SARB defined the NPS "as a set of instruments, procedures, and rules that enable funds to be transferred from one financial institution to another" (South African Reserve Bank, 2020). These definitions are important as they illustrate that the NPS comprises multiple components and is not the technology solution that its name would make it seem. The policies and rules included ensuring that the successful clearing of payments between banks is part of the NPS.

South Africa's NPS is regulated and supervised by the SARB (South African Reserve Bank, 2019). The SARB thus has the mandate to operate domestic and regional settlement systems and is responsible for maintaining the safety and efficiency of the NPS (South African Reserve Bank, 2019). In 1999, the SARB was mandated through the NPS Act for the Payments Association of South Africa (PASA) to be the management body for a payment system (PASA, 2022). In 2015, the SARB reviewed the NPS Act to examine the resilience and robustness of the NPS legislative and regulatory framework to ensure relevance (South African Reserve Bank, 2019). In March 2018, the SARB introduced the NPS Framework and Strategy Vision 2025 (just Vision 2025). This vision was for South Africa to maintain its world-class status by looking at 'safety', 'accessibility', and 'efficiency'.

It is envisioned in "Vision 2025" that by 2025, consumers will be more informed about payment services in an open and competitive market (South African Reserve Bank, 2018). "Vision 2025" will allow consumers to access the NPS through different mediums and channels, such as mobile devices and Internet

banking (South African Reserve Bank, 2018). This allows for payment innovations to access the NPS and be allowed to participate in the market. This indicates that the South African government is also embracing DFS payment solutions. The result is more DFS payment innovation which can assist in decreasing the cost of digital payments and making these transactions affordable.

According to the Global Index Database, as cited in a study by Demirgue-Kunt et al. (2017), growth in Fintech has been primarily driven by digital payments in South Africa (Slazus & Bick, 2022). Emerging Economies like South Africa are expected to have the highest adoption of Fintech and DFS solutions globally (Slazus & Bick, 2022). One of the critical priorities for Vision 2025 is financial inclusion through digital inclusion (Deloitte Africa & Mastercard, 2019). Furthermore, Vision 2025 sets out the imperative for the private and public sectors to collaborate to deepen financial inclusion, reduce reliance on cash, and encourage digital payment methods to achieve more inclusive and sustainable economic growth (Deloitte Africa & Mastercard, 2019). This demonstrates that the South African government supports providing financial services through digital channels.

2.3.5 *The South African Potential Adopter and Financial Inclusion: From Cash-Based to Digital Payment Systems*

Numerous studies on South Africa's payment and Fintech landscape have identified that South Africa has made significant strides in providing access to bank accounts. However, usage still remains low with many consumers using their accounts as mailboxes (Deloitte Africa & Mastercard, 2019; Financial Sector Conduct Authority & Genesis Analytics, 2022). In a study conducted by Deloitte and Mastercard (2019), cash in South Africa grew faster than inflation at 6 to 10 % despite access to DFS.

Digital Banking was also rising through various innovative measures introduced by South African banks, like mobile banking apps (Financial Sector Conduct Authority & Genesis Analytics, 2022). The high mobile penetration in South Africa has resulted in the convergence of Telecommunication companies with banks

and the establishment of Mobile Money Network Operators (MNOs) (Deloitte Africa & Mastercard, 2019).

Despite the increase in digital banking, South Africans still use cash, with the 2022 Global Payments Report indicating that 38% of the point-of-sale purchases in South Africa were conducted using cash (FIS, 2022). The Global Payments Report also found that South Africa had the most significant growth of POS expansion in the Middle East and Africa, with 22% growth in 2021 (FIS, 2022). South Africa's mobile wallet usage was low, with 5.1% and only 3% of real-time electronic transactions, despite 55% growth in real-time payment transaction volumes (FIS, 2022).

The previous sections have highlighted that South Africa has an enabling environment for DFS solutions with "fintechs", digital banks, high access to bank accounts, government support, and mobile penetration. Although this is the case, as this section illustrates, the usage and overall adoption of DFS solutions have been low compared to other emerging countries.

2.4 Theoretical Underpinnings of the Conceptual Model

As part of this study, a theory-based research model will be developed to understand the factors that can result in South Africans adopting and using DFS and what barriers prevent its adoption and usage.

A thorough review of various adoption theories is investigated by reviewing prior empirical research studies and using relevant theory to underpin the development of a conceptual model for the present study. The adoption literature comprises multiple models such as the Technology Acceptance Model (TAM) and the Theory of Planned Behaviour (TPB) (Madan & Yadav, 2016). Two main theories underpin the present study to ensure significant contributions through this research. These theories are the Technology Readiness Index (TRI) 2.0 and the Unified Theory of Acceptance and Use of Technology (UTAUT) 2.0. These two selected theories (TRI 2.0 and UTAUT 2.0) will be supplemented by the Resistance Theory for New Innovation.

2.4.1 *The Technology Readiness Index (TRI)*

The Technology Readiness Index (TRI) is a theoretical framework related to a person's predisposition to use, and one's general sentiments about, new technology (Humbani & Wiese, 2019; Parasuraman, 2000). This theoretical model determines that technology will trigger negative and positive feelings, which vary amongst people and result in changing results in people's propensity to adopt new technologies (Parasuraman & Colby, 2015). The feelings result from eight paradoxes identified by the theoretical model, namely "freedom/enslavement", "assimilation/isolation", "efficiency/inefficiency", and "control/chaos", through which an individual can trigger both positive and negative feelings (Parasuraman, 2000; Parasuraman & Colby, 2015).

Combining positive and negative feelings about technology is crucial to technology readiness (Parasuraman, 2000). This is because positive feelings can drive technology adoption, while negative feelings can cause barriers and thus be inhibiting. The TRI model identified four constructs and grouped them into Driving and Inhibiting Factors (Humbani & Wiese, 2019; Parasuraman & Colby, 2015). Optimism and Innovativeness are constructs that are drivers of technology adoption and therefore are Driving Factors, whereas Discomfort and Insecurity are Inhibiting Factors (Humbani & Wiese, 2019; Parasuraman & Colby, 2015).

In 2019, Humbani & Wiese (2019) extended the TRI to create TRI 2.0. This change resulted from the changing landscape in mobile payment technologies, super high-speed access, social media, and cloud computing (Parasuraman & Colby, 2015). The changes to TRI included four additional constructs, namely Convenience, Compatibility, Perceived Cost, and Perceived Risk, to the original TRI model (Humbani & Wiese, 2019). These four constructs have been found to have a relationship with mobile banking adoption. Convenience and Compatibility are positive determinants, whereas Perceived Cost and Perceived Risk have been found to potentially inhibit the adoption of new technologies (Humbani & Wiese, 2019). The TRI 2.0 can address technology readiness within a particular demographic group and can be used to understand consumer dynamics behind technology adoption (Parasuraman & Colby, 2015).

The TRI 2.0 model can thus assist in determining the dynamics behind DFS adoption in South Africa by identifying the Driving and Inhibiting factors for the present study. The ever-changing environment of DFS in South Africa makes this model effective in identifying the individual differences between drivers and inhibitors as potential determinants of individual-level DFS adoption. To create an in-depth view, the UTAUT will be combined with this theory to underpin the conceptual model for the present study.

2.4.2 *The Unified Theory of Acceptance and Use of Technology (UTAUT)*

The Unified Theory of Acceptance and Use of Technology (UTAUT) was developed as a comprehensive synthesis of prior technology acceptance research. This model is used frequently to examine the user adoption intentions related to new Information Technologies (ITs). The model is made up of four constructs, namely Effort Expectancy (EE), Performance Expectancy (PE), Facilitating Conditions (FCs), and Social Influence (SI) (Madan & Yadav, 2016; V. Venkatesh et al., 2012). According to the UTAUT, PE, EE, and SI influence behavioural intention, while behavioural choice and FCs determine technology use (Venkatesh et al., 2012).

In Venkatesh et al. (2012), the UTAUT is adapted to investigate consumer technology acceptance by redefining the aforementioned constructs. This definition allows the study conducted to examine consumer adoption of technology. An investigation conducted by Venkatesh et al. (2012) showed that many articles cited the original UTAUT model as a reference to the body of work for adoption. Madan & Yadav (2016) extended the UTAUT and created the UTAUT 2 theoretical model to improve the parsimony and robustness of the original. This new extended model included three additional constructs, namely Perceived Value (PV), Hedonic Motivation, and Habit. However, even with the inclusion of these additional constructs, the UTAUT 2 model is not without its limitations. Madan & Yadav (2016) observed that one major limitation of the UTAUT 2 model is the need to incorporate the role of culture in adopting IT/IS.

The use of UTAUT 2 and TRI 2.0 models to underpin the present study would enable an empirical investigation of determining factors most likely to influence the adoption of DFS in the context of South Africa. The robustness of these models ensures that additional constructs can enable and provide a more robust analysis of DFS adoption inhibitors and drivers from a multi-theoretical perspective, where one theory could potentially offset the limitations of the other. Furthermore, the present study will incorporate the Resistance Theory for New Innovations to enhance and supplement the combination of the UTAUT 2 and TRI 2.0 models.

2.4.3 *Resistance Theory for New Innovations*

According to Ram & Sheth (1989), “Innovation Resistance is the resistance offered by consumers to an innovation, either because it poses potential changes from a satisfactory status quo or it conflicts with their belief structure.” The theory determines two barriers that can result in a consumer not adopting innovations like DFS in a cash-based country. The study by Ram & Sheth also finds innovation resistance to be a normal instinctive response by consumers. Therefore, it is essential to understand the process of addressing and overcoming the resistance caused by barriers (Ram & Sheth, 1989). Functional Barriers and Psychological Barriers are the two barriers which can be experienced by consumers (Ram & Sheth, 1989).

Functional Barriers are made up of three areas, namely product usage patterns, product value, and risks, associated with product usage (Ram & Sheth, 1989). The study found that these barriers arise if consumers perceive significant change from adopting innovation. Psychological Barriers are made up of two factors, namely the traditions and norms of the consumer, and perceived product image (Ram & Sheth, 1989). The study found that these barriers are created through conflict with consumers’ beliefs before the innovation (Ram & Sheth, 1989).

Psychological Barriers, particularly the traditions and norms, concern the cultural change created for the consumer by an innovation. Deviation from existing cultural norms creates a barrier, and the more excellent the variation, the greater

the barrier and thus resistance (Ram & Sheth, 1989). Incorporating this theory as part of the study's analysis and investigation allows the study to consider Culture, which is not included in the UTAUT model. The Resistance Theory for New Innovation will also supplement the UTAUT 2.0 and TRI 2.0 to include factors impacting resistance by South African consumers to using DFS.

2.4.4 *Review Journal Articles*

The present study reviewed relevant journal articles from 2010 to 2022 and identified 16 prior studies focussed on DFS and Fintech intention and adoption behaviours in emergent markets. It was found that 44% of the studies reviewed were from 2022, 6% from 2021, 19% from 2020, 19% from 2019, 6% from 2016, and 6% from 2010. The gap in 2021 can be attributed to the pandemic in 2020 and increase in studies found in 2022. Most of the studies were quantitative, with one being a mixed method (interviews and surveys) study, whereas two were classified as cross-sectional quantitative studies. The countries covered in these studies were Bangladesh (2), India (1), Indonesia (2), Jordan (1), Malaysia (2), Pakistan (1), and South Africa (3) (the numbers in brackets denote the studies attributed to each country). In these studies, researchers used a number of adoption models, including the Extended Valence Framework (EVF), Social Cognitive Theory (SCT), Technology Acceptance Model (TAM), Technological Personal Environment Model (TPE), Theory of Planned Behaviour (TPB), and Unified Theory of Acceptance and Use of Technology (UTAUT). The TAM and UTAUT were the most used adoption models, with some studies where both were used to inform empirical analyses.

Appendix A provides a summary of the prior studies reviewed and discussed below, with details of the technology adoption determinants studied.

Perceived Usefulness (as per the TAM model) or Performance Expectancy (as per the UTAUT model) significantly and positively influences the adoption of DFS and Fintech services by influencing attitude according to the reviewed studies (Khan & Siddiqui, 2019; Mazambani & Mutambara, 2020; Nkoyi et al., 2019; Singh et al., 2020; Slazus & Bick, 2022; Urus et al., 2022). South Africans were more likely to adopt Fintech services if it made their lives simpler and more

accessible (Slazus & Bick, 2022). According to Shahzad et al. (2022), Perceived Usefulness did not impact attitudes and behavioural intention in Malaysia (Shahzad et al., 2022). Perceived Ease of Use (as per the TAM model) or Effort Expectancy (as per the UTAUT model) also positively influence the intention to adopt DFS and Fintech services (Khan & Siddiqui, 2019; Mazambani & Mutambara, 2020; Nkoyi et al., 2019; Shahzad et al., 2022; Singh et al., 2020; Slazus & Bick, 2022). Interestingly, some studies determined that Effort Expectancy is not an indicator for DFS and Fintech service adoption among Bangladeshi, Malaysian, and Indonesian graduates (Hassan et al., 2022; Urus et al., 2022), which differs from a previous study from Shahzad et al. (2022) which investigated the impact of COVI-19 on Malaysian respondents behavioural intention to adopt.

According to Pal et al (2020), Network Externalities is closely related to Social Influence, which has gained popularity in IT adoption models (Pal et al, 2020). The close relationship between Network externalities and Social Influence noted above allows this study to incorporate the above literature findings into our study of Network externalities. Network Externalities and Social Influence are both concerned with the usage of technology by people within the user's social circle (Pal et al., 2020; Qasim & Abu-Shanab, 2016). A study by Lee et al (2019) determined that Network Externality can be split into two components, namely Direct Network Externality and Indirect Network Externality, respectively. Direct Network Externality is defined as a user's value increasing when they believe there are more users of the product or services. Indirect Network Externality is the "increase in the number of users and additional value or utility that users gain when additional complementary products or services are added" (Lee et al, 2019, p. 9). The present study reviewed Direct Network Externality as it meets the Network Externalities definition. The existing literature reviewed identified that Network Externalities has a significant positive effect as a predictor of behavioural intention and attitudes towards adoption.

Social Influence as a construct has various effects on adoption intention behaviour. In Bangladesh, Pakistan and Malaysia, this factor was also found to correlate positively as their peers, friends, and family's opinions inspire people

(Hassan et al., 2022; Khan & Siddiqui, 2019; Shahzad et al., 2022), while for Malaysian recent graduates, a further study determined that Social Influence was not an indicator of behavioural intention (Urus et al., 2022). In India and Indonesia, Social Influence was identified to negatively impact behavioural intention to adopt DFS or “fintech” services (Singh et al., 2020; Urus et al., 2022). The close relationship between Network externalities and Social Influence detailed above allows this study to incorporate the above literature findings into our study of Network externalities.

Trust was determined to be an enabler and inhibitor in South Africa, with a lack of trust or perceived risk resulting in the lack of adoption of “fintech” (Slazus & Bick, 2022). Internationally, trust was significantly correlated with behavioural intention, and therefore trust towards the service provider or “fintech” technology plays a significant role in using the technology to transact (Alhajjaj & Ahmad, 2022; Hassan et al., 2022; Kurniasari et al., 2022; Shahzad et al., 2022; Urus et al., 2022). Trust does not only impact behavioural intention to adopt “fintech” services or DFS directly. For instance, an Indonesian study determined that Trust improves the usefulness of services and thus increases the perceived usefulness due to the positive relationship between these two factors (Meyliana et al., 2019). Due to the Secondary and Direct influence detailed above, trust is determined to have an influence on adoption intention behaviour.

Perceived Risk was determined to inhibit Behavioural Intention as it negatively relates to this particular outcome (Mahmud et al., 2022; Slazus & Bick, 2022; Xie et al., 2021). There are mixed findings on the impact of this factor. Some prior studies have determined that perceived risk has a negative impact on behavioural intention to adopt technology (Xie et al., 2021). Interestingly, in other studies, perceived risk did not influence behavioural intention and was not found to mediate between trust and behavioural intention (Hassan et al., 2022; Meyliana et al., 2019). The perceived value of technology is affected by the combination of performance expectancy, effort expectancy, and perceived risk (Mahmud et al., 2022; Xie et al., 2021). Prior studies noted a positive relationship between Perceived Value and behavioural intention to adopt technology (Mahmud et al., 2022; Xie et al., 2021).

Prior studies determined that Facilitating Conditions in emerging economies like Bangladesh or India have been identified as significantly influencing behavioural adoption intention (Hassan et al., 2022; Madan & Yadav, 2016). Interestingly, some studies determined that Facilitating Conditions did not significantly impact behavioural adoption in emerging countries like Indonesia (Kurniasari et al., 2022; Pal et al., 2020; Xie et al., 2021). Although this was the outcome for India and Indonesia, the study in Indonesia noted the limitations of their population group having access to digital infrastructure and hence Facilitating conditions not having an impact (Kurniasari et al., 2022). In another study in India by Pal et al. (2020), the unavailability of these facilitating conditions was investigated as a barrier to adoption (Pal et al., 2020). The study did not find a relationship between the unavailability of facilitating conditions and adoption. In this study, the population's access to online digital infrastructure was cited as a reason for the lack of a relationship (Pal et al., 2020).

In Humbani & Wiese's (2019) study, Perceived Cost was adapted from Kim (2010), which used Perceived Fee. Therefore, for this study perceived fee will be investigated under Perceived Cost. The reviewed literature on Perceived Cost identified a significant negative relationship between Perceived Cost and the behavioural intention to adopt technology (Humbani & Wiese, 2019; Kim, 2010; Slazus & Bick, 2022). The prior studies highlighted that service providers should look at having low costs to facilitate adoption for technology in South Africa (Humbani & Wiese, 2019; Slazus & Bick, 2022). This finding was similar to research on other countries like South Korea and China, which found low cost to facilitate user technology adoption behaviour (Kim, 2010; Zhou, 2011).

2.5 Development of the Conceptual Model

The constructs constituting the conceptual model developed for the present study are grouped into Facilitators and Barriers as enablers (drivers) and inhibitors, respectively. According to Humbani & Wiese (2019), drivers positively influence the adoption of new technologies. In the context of the present study, these drivers will positively impact the adoption of Digital Financial Systems (DFS). In addition, according to the Resistance to Innovation Theory, "customers face

several barriers that paralyse their desire to adopt innovations" (Ram & Sheth, 1989). Therefore, considering the present study, this paralysis presents potential "Barriers" that negatively influence the intention to adopt DFS.

2.5.1 *Behavioural Intention to Adopt Digital Financial Systems (DFS)*

This variable "measures the intensity with which an individual intends to perform a specific behaviour" (Madan & Yadav, 2016; Fishbein & Ajzen, 1975), which in this case, is the adoption of DFS. In the study by Madan and Yadav (2016), this variable was a dependent variable impacted by various factors. Similarly, in the context of the present study, Behavioural Intention to Adopt Digital Financial Systems (DFS) is examined as the dependent variable affected by a set of independent variables discussed in Sections 2.5.3 (Facilitators) and 2.6.3 (Barriers).

2.5.2 *Facilitators of Digital Financial System (DFS) Adoption*

a. *Performance Expectancy (PE)*

PE is "the degree to which technology will benefit consumers in performing certain activities" (V. Venkatesh et al., 2012). Regarding DFS, PE may be seen as the degree to which customers perceive that using technology (DFS) as an alternative to cash will improve and speed up their performance while making payment purchases. This variable is underpinned by the UTUAT and UTAUT 2 theoretical models. It positively influences behavioural intention to adopt technology, as an increase in PE in turn causes an increase in behavioural intention (Madan & Yadav, 2016; V. Venkatesh et al., 2012). According to Madan and Yadav (2016), numerous researchers (e.g., Slade et al., 2015; Yan & Yang, 2015) have considered the role of this variable as a factor in mobile wallet adoption as a type of DFS. Therefore, the following hypothesis is proposed:

H1: PE will positively influence the behavioural intention to adopt DFS

b. *Effort Expectancy (EE)*

Effort Expectancy (EE) is defined as “the degree of ease associated with consumers’ use of technology” (V. Venkatesh et al., 2012). In the context of DFS, EE is the degree to which consumers expect DFS payment solutions to be free from effort and easy enough to learn to adopt in their daily lives. EE is underpinned by the UTUAT and UTUAT 2 theoretical models and is theorised to influence behavioural intention to use technology (Madan & Yadav, 2016; V. Venkatesh et al., 2012). According to Madan and Yadav (2016), numerous studies have included this variable as a factor in technology adoption (e.g., Wang & Yi, 2012; Kim et al., 2010). Therefore, the following hypothesis is proposed:

H2: EE will positively influence the behavioural intention to adopt DFS

c. *Network Externalities*

Network Externalities is “the variable that captures technology usage by people in the consumer’s social circle” (Pal et al., 2020; Qasim & Abu-Shanab, 2016). This variable is closely related to Social Influence which is found in the UTAUT and UTAUT 2 theoretical models. It is defined as how a consumer’s family, relatives, or friends affect their decisions to use a product or service (Madan & Yadav, 2016; Riquelme & Rios, 2010). DFS payments solutions can create an environment where consumers can pay each other using technology platforms, thus creating a collaborative environment (Pal et al., 2020). Network Externalities is the extent to which DFS solutions create a collaborative environment through adoption by a consumer’s social circle (family, relatives, or friends). Therefore, the following hypothesis is proposed:

H3: Network Externalities will positively influence behavioural intention to adopt DFS

d. *Facilitating Conditions*

Facilitating Condition (FC) is defined as “the degree to which users know that they can use technology because there are supporting resources” available to them in their usage environment (V. Venkatesh et al., 2012). In this study, FC is

the availability of suppliers that allow for the usage of DFS when conducting purchase payments. Unavailability of FC is a barrier found in The Resistance Theory of New Innovation and is determined to have a negative impact on usage intention (Pal et al., 2020). According to Pal et al. (2020), studies in emerging environments (Mostafa & Eneizan, 2018; Verkijika, 2018) and low-income groups (Raleting & Nell, 2011) identified FC as variables impacting technology adoption. Pal et al. (2020) focused on unavailability, which hurt adoption. The availability of FC will have an opposite effect. Therefore, the following hypothesis is proposed:

H4: FC will positively influence behavioural intention to adopt DFS

e. ***Perceived Value***

PV is "the value consumers perceive they are to receive in exchange for the price they pay to be provided with a product or service" (Madan & Yadav, 2016). In the present study, this variable can be defined as the trade-off between the value consumers gain when using DFS compared to the cost they are paying for it (Zeithaml, 1998; Madan & Yadav, 2016). PV is a variable found in the UTUAT 2 model and that significantly influences adoption (Madan & Yadav, 2016). According to Madan and Yadav (2016), this factor has had numerous research which found it to be critical when investigating technology adoption (Slade et al., 2015; Amoroso & Magnier-Watanabe, 2012; Pagani, 2004). Therefore, the following hypothesis is proposed:

H5: PV will positively influence behavioural intention to adopt DFS

f. ***Price Benefit***

PB is "the afforded benefits compared to alternatives available, including reduced costs" (Pal et al., 2020). In the context of the present study, PB is the cost benefits that the consumer receives for adopting and using DFS. PV is a variable used as a facilitator in the research model created for investigating the usage of mobile payment services in developing countries (Pal et al., 2020). Pal et al. (2020) also noted that in low-income sections of emerging markets, consumers might not be willing to pay for technology compared to cash, which is a low-cost medium of transacting (Heeks & Kenny, 2002; Pal et al., 2020). According to Pal et al.

(2020), the situation is different when there is a cost advantage provided by suppliers using discounts to promote their DFS solutions. These cost benefits received from suppliers therefore provide a financial advantage to consumers, which should result in adoption. Thus, the following hypothesis is proposed:

H6: PB will positively influence behavioural intention to adopt DFS

g. ***Trust***

Trust relates to the trustworthiness of the system (Pal et al., 2020; Qasim & Abu-Shanab, 2016). Trust signifies consumers' reliability in DFS solutions in the present study's context. Trust is a construct underpinned by the Resistance Theory for New Innovations and is found to be essential for solutions to monetary transactions (Pal et al., 2020; Qasim & Abu-Shanab, 2016). Numerous studies (e.g., Kesharwani & Singh Bisht, 2012; Malaquias & Hwang, 2016) have been conducted on trust where it has been determined that trusting the service provider is essential in emerging environments like Brazil, Kenya, and India (Pal et al., 2020). According to Lawrence and Tar (2010), consumers are reluctant to share their sensitive personal information and bank details with technology platforms they do not trust. This lack of sharing indicates that consumers cannot use these platforms to conduct payment transactions. Thus, trust can influence DFS adoption. Therefore, the following hypothesis is proposed:

H7: Trust will positively influence behavioural intention to adopt DFS

2.5.3 *Barriers to Digital Financial Services (DFS) Adoption*

a. ***Unavailability of Facilitating Conditions***

Facilitating Conditions (FC) in the present study can be interpreted as comprising facilitator and barrier dimensions. As a barrier, this variable denotes the absence of FC. Therefore, in the present study, the Unavailability of Facilitating Conditions (UFC) will denote the absence of suppliers that allows for the usage of DFS when conducting purchase payments. UFC is a construct underpinned by the Resistance Theory for New Innovations and has been observed to have the opposite effect of FC on adoption intention behaviours (Pal et al., 2020). For

instance, in most countries, DFS requires an Internet connection, whether a point of sale (POS) device that allows card swiping or a mobile application to conduct a transaction (Pal et al., 2020). This DFS requirement can present a barrier in emerging economies as the existing facilitating infrastructure is poor (Ameen & Gorman, 2009; Avgerou, 2008; Pal et al., 2020). Therefore, the following hypothesis is proposed:

H8: UFC will negatively influence behavioural intention to adopt DFS

b. ***Perceived Risk***

Perceived Risk (PR) is described as "consumers perceiving a certain amount of risk in an electronic financial transaction" (Lu et al., 2011; Pal et al., 2020). PR in mobile banking is defined as the consumer's belief that a digital financial transaction is vulnerable to uncertainty (Li et al., 2019; Shao et al., 2019; Pal et al., 2020). Therefore, in the context of the present study, this definition of PR used in mobile banking will be adopted. PR is also classified as a barrier according to the Resistance Theory for New Innovations (Pal et al., 2020). Studies conducted on PR determined that news related to digital fraud and digital crimes has caused an increase in PR (Palm Herath, De' &Rao, 2018; Pal et al., 2020). Kim, Zoo, Lee, and Kang (2018) observed that in emerging economies, the risk of such a monetary loss could present a barrier to adoption due to high price sensitivity (Pal et al., 2020). This barrier can negatively influence adoption. Therefore, the following hypothesis is proposed:

H9: PR will negatively influence behavioural intention to adopt DFS

c. ***Perceived Cost***

According to Mallat (2007), the cost of using a DFS can negatively impact consumers adopting mobile payments (Humbani & Wiese, 2019). Mallat (2007) also found that consumers resent mobile payment platforms that charge the consumer for payment transfers (Mallat, 2007; Humbani & Wiese, 2019). Therefore, in the context of the present study, PC is the cost that the consumers believe they have to incur for the use of DFS. The perceived cost which results in this resentment has necessitated that the construct is classified as an inhibitor

underpinned by the Technology Readiness Index (Humbani & Wiese, 2019). In the study by Humbani & Wiese (2019), they observed that inhibitors were determined to have a negative impact on adoption. Therefore, the following hypothesis is proposed:

H10: PC will negatively influence behavioural intention to adopt DFS

2.5.4 *The Conceptual Model of the Study*

The study's conceptual model is underpinned by the Technology Readiness Index (TRI), the Unified Theory of Acceptance and Use of Technologies (UTAUT) 2.0, and the Resistance Theory of New Innovations.

This conceptual model is developed to examine the relationships between a set of facilitators and barriers as the independent variables and the dependent variable of the study Behavioural Intention to Adopt Digital Financial Systems (DFS), as shown in Figure 5.

Figure 5 shows the seven facilitator's Performance Expectancy, Effort Expectancy, Network Externalities, Facilitating Conditions, Perceived Value, Trust, and Price Benefit, and three barriers Perceived Risk, Unavailability of Facilitating Conditions, and Perceived Cost, that are hypothesised as determinants related to Behavioural Intention to Adopt DFS.

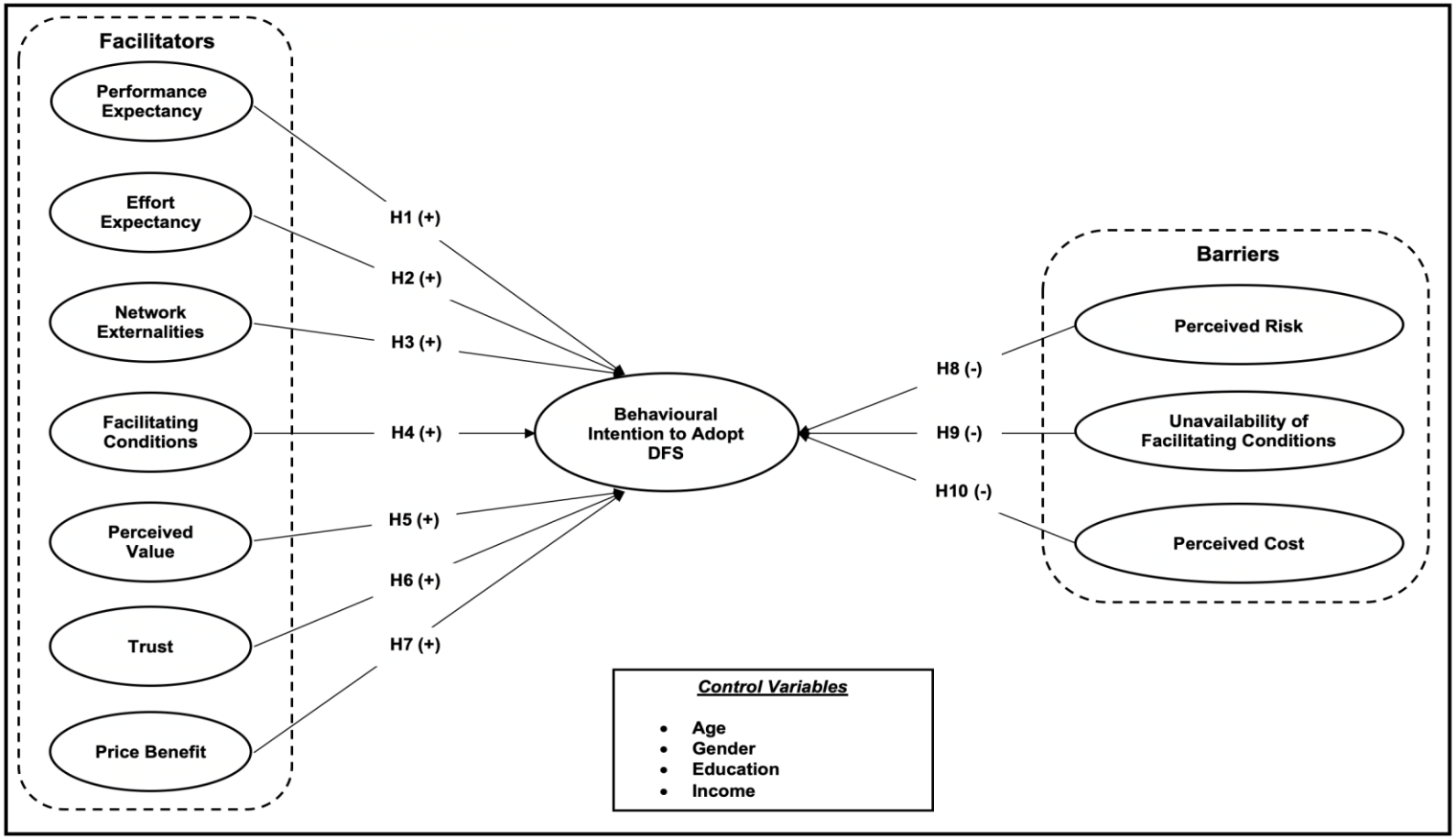

Figure 6: The Research Model

2.6 Conclusion

This chapter reviewed the theoretical literature on the evolution of digital financial systems (DFS) and its role in South Africa. The concept of DFS was introduced through a review of global trends and the impact of DFS in Sub-Saharan Africa. Next, DFS was discussed in further detail in relation to the context of South Africa. Subsequently, the system of social grants in South Africa was described. The potential for DFS adoption in South Africa was discussed with a focus on digital payments before a review of existing technology adoption models. The existing literature on technology adoption theories and related models was also reviewed. The UTAUT model was then expanded by identifying and exploring facilitating and inhibiting factors that can be considered to affect the behavioural intention to adopt DFS in the South African context. The conceptual model's hypotheses were developed to test the relationship between a set of independent variables and intention to adopt DFS as the dependent variable of the study.

CHAPTER 3. RESEARCH METHODOLOGY

3.1 Introduction

In Chapter 2, the relevant literature was presented, and a conceptual model developed with hypothesis formulated for the present study. A set of determinants were predicted to influence individual DFS adoption in South Africa. This chapter describes the study's research design strategy and approach, as well as data collection methods used. The study's sample and sampling methods are described followed by data collection methods. Next, construction of the study's research instrument and its administration is described. Data Analysis strategies are also discussed, followed by instrument validity and reliability issues. Thereafter, the study's limitations are discussed with ethical considerations. Lastly, the chapter is concluded.

3.2 Research approach

According to Apuke (2017), "Quantitative Research is about utilising and analysing numerical data using statistical methods or techniques to answer questions like who, how much, what, where, when, how many, and how". As this study poses "what" questions to determine factors influencing behavioural intention, it uses the quantitative approach to quantify and analyse a set of independent variables to understand their relationships with a dependent variable (Apuke, 2017). The present study used existing literature to define a conceptual model to depict the relationships between these independent variables and the dependent variable Behavioural Intention to Adopt Digital Financial Systems (DFS). The study's conceptual model was developed to empirically test DFS adoption behaviour and its determining factors among a specific subset of South Africa's citizens. This type of investigation lent itself to quantitative research methodology, which is focused on objectively measuring social behaviour (Apuke, 2017).

3.3 Research design

Survey Research is a type of quantitative research method that uses scientific sampling techniques with a structured questionnaire to measure a given population's characteristics through statistical methods (Apuke, 2017; Sukamolson, 2007). Data were gathered to test the developed conceptual model using the structured questionnaire as the research instrument of choice. The variables were identified using the literature highlighted in this study. The tested variables were used to predict Behavioural Intention to Adopt DFS.

3.4 Data collection methods

Multiple options can be used for data collection. As the present study involves survey-based research, the data collection instrument used was a questionnaire. This survey instrument contained structured and close-ended questions to allow data from a substantial population sample to be pooled across different locations. It provided for generalisation in the study (Creswell, 2009). A questionnaire will enable adding a numerical value to understand the relationship between independent and dependent variables. Each variable being tested via the survey instrument was adopted from the existing technology adoption literature. As data were collected at a particular point in time, this study was cross-sectional (Rajulton, 2001). The survey was administered to respondents using a participant information sheet (Appendix B) and with a research instrument containing Likert questions (Appendix C) to ensure that the data collected could be empirically examined.

3.5 Population and sample

3.5.1 *Unit of Analysis*

The unit of analysis is a classification of the specific unit to be sampled (Terre Blanche et al., 2008). The present study's targeted sample consists of South African adopters who are SASSA social grant holders. The unit of analysis (target

respondent) is a data point. Thus, data were surveyed from these data points using a survey instrument (questionnaire).

3.5.2 *Population*

There are approximately 11 million SASSA social grant beneficiaries in South Africa. A proportion of 58% (about 6 million) of these recipients are cardholders who use linked bank accounts as mailboxes into which their social grants are deposited (Financial Sector Conduct Authority & Genesis Analytics, 2022). Moreover, 2% of these recipients have inactive SASSA accounts (Financial Sector Conduct Authority & Genesis Analytics, 2022). These cardholders use traditional cash-based payment mechanisms in their daily transactions.

Notably, South Africa was found to have a mobile access penetration rate of 95% as of 2018 (Silver et al., 2019). As a percentage of the overall population, this represents the number of individuals who have regular access to a mobile phone, even if they do not personally own one. This figure is observed against a backdrop of 103 million registered mobile phone subscribers in South Africa in 2021, which accounts for approximately 89.4% of the total households in South Africa who had access to mobile devices in 2021 (ICASA, 2022).

The researcher targeted a population of SASSA social grant beneficiaries for this study. Although subject to further analysis of the South African context, this consideration is informed by the assumption that SASSA social grant cardholders who use mobile phones in their daily lives potentially represent (1) a significant segment of the population that is financially excluded from Digital Financial Systems (DFS) yet (2) could potentially adopt digital payment mechanisms either through their enabled cards which can be used to make payments or using their mobile phones as payment tools (Financial Sector Conduct Authority & Genesis Analytics, 2022) to enable their financial inclusion.

3.5.3 *Sample*

The sampling stage of this study unfolded in two phases. The first phase entailed identifying communities from which a sample could be selected. The second

phase involved describing the sampling approach used to collect data. A cross-section of SASSA social grant beneficiaries who are cardholders and potential registered mobile phone subscribers in selected South African communities were pooled as a sample for the present study. This cross-section was determined by their presence in regions where participation in the SASSA social grant scheme is most prevalent.

The present study was conducted in peri-urban communities in the OR Tambo District Municipality in the Eastern Cape. This district municipality comprises five local municipalities and is ranked the most populous municipality in the Eastern Cape and fourth in the country (OR Tambo District Municipality, 2021). According to the Poverty Ranking of South Africa's district, OR Tambo ranked first with people living in extreme poverty (OR Tambo District Municipality, 2021). In 2018, OR Tambo had an estimated 1.51 million people totaling 2.6% of South Africa's population (IHS Global 2018 Population Report cited in OR Tambo District Municipality, 2021).

Poverty lines are an estimated imaginary line developed as a tool which allows for statistical reporting of poverty levels and patterns (Statistics South Africa, 2019). In 2018, the lower and upper bounds of the poverty line in South Africa ranged between R 785 and 1,183 (Statistics South Africa, 2019). In 2018, 1.21 million people were living in poverty in OR Tambo District Municipality according to the upper poverty line threshold (OR Tambo District Municipality, 2021). This municipality was selected for the present study as high poverty results in a large population having to rely on social grants, which can contribute to poverty reduction (Garidzirai & Chikuruwo, 2020).

The present study was conducted in the King Sabata Dalindyebo Local municipality, while the pilot for this study was conducted in Port St. Johns Local Municipality. The study first piloted the study's prepared research instrument with SASSA grant holders in Port St Johns. Port St Johns was selected as it would have been challenging to separate pilot responses and the actual study respondents if they were chosen from the KSD Local Municipality.

The next section provides a background of the targeted local municipality for the pilot and main study in the OR Tambo District and KSD Local municipalities, respectively.

a. ***King Sabata Dalindyebo (KSD) Local Municipality***

The KSD Local Municipality is located South-West of the OR Tambo, with Mthatha being the central city and economic centre of OR Tambo District (OR Tambo District Municipality, 2021). The KSD Local Municipality contains urban and rural settlements (OR Tambo District Municipality, 2021). The KSD Local Municipality had the least amount of people living in poverty in the OR Tambo District in 2018, with 71.7% (OR Tambo District Municipality, 2021). This locality which contains the least amount of people among the five local municipalities, still has a population higher than 70%. This, thus, reinforces why OR Tambo District municipalities scored first in the country overall for poverty (OR Tambo District Municipality, 2021).

b. ***Port St. Johns Local Municipality***

The Port St. Johns Local Municipality is a Coastal municipality. An urban town, Port St Johns is known for its tourism due to its beaches and the Umzuvubu Mouth (OR Tambo District Municipality 2021). This locality is the only urban town and regional economic centre of the local municipality (OR Tambo District Municipality, 2021). The local municipality has approximately 90% of its citizens dwelling in traditional tribal dwellings and is, thus, rural (OR Tambo District Municipality, 2021). According to the upper poverty line definition (OR Tambo District Municipality, 2021), Port St Johns has the most significant number of people living in poverty, with an observed 86.7%.

3.5.4 *Sampling method*

A sampling decision informed by the context and objectives of this study was made. The context involves communities of SASSA social grant beneficiaries who are cardholders and potential mobile phone subscribers. The goal of this study is to examine the role of social grant beneficiaries as potential adopters of

digital payment tools through their SASSA cards or access to mobile phones. Complemented by relevant national statistics, this was considered in identifying an appropriate sample. As such, background information on population characteristics can be used to arrive at a decision (Henry, 1990; Neuman, 2003). This is a component of “judgmental” or “purposive” sampling, whereby a sample is selected based on the informed judgment of how representative or valid a sample is likely to be (Babbie, 2004). In addition, the chosen regions were in correspondence with communities where participation in the SASSA social grant scheme is most prevalent. This involved a “random selection” component, whereby each respondent targeted had an equal chance of selection, independent of other occurrences in the selection process (Babbie, 2004). For statistical inference to be possible in the present study and to enhance the proposed conceptual model's explanatory (predictive) power, a minimum sample ratio of 5:1 or five observations per independent variable is acceptable. However, a more preferred ratio is 20 observations for each independent variable (Hair et al., 2010). As the number of independent variables in the conceptual model developed for the present study equals 10, this threshold would yield a minimum sample size of at least 200 respondents (n = 200). As such, in the considered view of the researcher, a pooled sample comprising a cross-section of at least 200 SASSA cardholders was drawn from the target population of social grant scheme beneficiaries nationwide.

3.6 The research instrument

Eleven constructs, namely “Performance Expectancy”, “Effort Expectancy”, “Network Externalities”, “Facilitating Conditions”, “Perceived Value”, “Trust”, “Price Benefit”, “Perceived Risk”, “Unavailability of Facilitating Conditions”, and “Perceived Cost”, and “Behavioural Intention to Adopt DFS” were measured in the study. These constructs were measured using a multi-item, five-point Likert scale to ensure instrument consistency. Its use enables target respondents indicate their levels of agreement or disagreement with a given statement (Clark-Carter, 2009) used to measure a particular construct dimension. The measurement scale used for each construct ranged from “1= strongly disagree” to “5 = strongly agree”. Likert scales are respondent-friendly and allow for

responses to be coded. Further, they are reliable for measuring human behaviour indicators (Oliver & Linda, 1981). Each instrument variable consisted of three to four items from measurement scales validated in prior literature and adopted to inform the study's context.

Instrument Measures			
Variable	**Hypotheses**	**No. of Dimensions (all scale items measured on a 5-point Likert scale)**	**Existing Literature Source**
Performance Expectancy	H1	4	(V. Venkatesh et al., 2012)
Effort Expectancy	H2	4	(Madan & Yadav, 2016; V. Venkatesh et al., 2012)
Network Externalities	H3	3	(Pal et al., 2020)
Facilitating Conditions	H4	4	(V. Venkatesh et al., 2012)
Perceived Value	H5	3	(Kuo et al., 2009)
Trust	H6	4	(K. C. Lee & Chung, 2009; Zhou, 2011, 2013)
Price Benefit	H7	3	(Pal et al., 2020; V. Venkatesh et al., 2012)

Perceived Risk	H8	4	(Featherman & Pavlou, 2003; Mallat, 2007)
Unavailability of Facilitating Conditions	H9	3	(Gu et al., 2009; Pal et al., 2020; V. Venkatesh et al., 2012; Zhou et al., 2010)
Perceived Cost	H10	3	(Kim, 2010)
Behavioural Intention	H11	3	(Slade et al., 2015; V. Venkatesh et al., 2012)

Table 4: Research Instrument

Using a structured questionnaire as the research instrument of choice for the study was deemed advantageous. First, the questionnaire was cost-effective and convenient to develop. Second, a physical survey was determined to be the best approach, ensuring that respondents had access to the research instrument (questionnaire). Questionnaires are suitable for measuring attitudes and perceptions and allowing for precise information to be elicited using close-ended questions. In conducting a physical survey, the researcher catered for respondents who did not have access to any other digital online platforms. The final version of the questionnaire is shown in Appendix B. The following section specifies the survey method for administering the research instrument (questionnaire).

3.7 Procedure for data collection

The instrument was shared with quantitative research experts to ensure that it was of good quality and critically evaluated before pre-testing. Once this was completed, the researcher conducted a pre-test among respondents with similar

characteristics to the identified target population to ensure the instrument's content validity. The respondents were explicitly asked to comment on whether the questions made sense and wording, provide feedback on any gaps they identified, as well as critically evaluate the questionnaire. Their feedback was incorporated with minor modifications to the questionnaire being made.

Two hundred and fifteen (215) questionnaires were administered during the survey conducted in the OR Tambo District Municipality. The researcher contacted three research assistants to distribute copies of the questionnaires and collect data. The appointed research assistants were informed of the study's objectives and the targeted population group. In preparation for the survey, the research assistants were informed that the study is voluntary and that only recipients of social grants can participate. They were also instructed as to the various locations where the questionnaire should be distributed to respondents.

The survey was administered from December 1st to 9th 2022. This period was selected as it coincided with the period during which SASSA provided grant collection to its customers in December (December 5th 2022). The researcher and assistants visited places where grants can be collected in the KSD Municipality, like the Post Office, Banks, and malls and targeted various suburbs like Southern Wood in Mthatha, to collect data. Respondents were asked to participate in the survey. Where respondents declined to participate, the researcher and assistants moved on to other participants. Each respondent was then provided with the research instrument and a cover letter. The cover letter included contact information, an explanation of the study being conducted, and instructions on completing the questionnaire.

The cover letter was prepared as per the University of Witwatersrand's ethics committee guidelines. Issues concerning survey participation, confidentiality, and anonymity were addressed, and all of the university's required processes were followed. Respondents were also verbally notified that the survey was anonymous. Hence, their names were not needed, and they could quit the survey without being adversely affected.

3.8 Data analysis and interpretation

Data Analysis was conducted using these statistical tools, namely Microsoft Excel, IBM SPSS (Version 28) and SmartPLS (Version 4). Data Analysis, therefore, occurred in the following four stages:

Stage 1: Data Screening

The collected data were transferred to Microsoft Excel to determine overall completeness and upload to IBM SPSS. Instrument items were classified and assigned numerical codes for quantitative analysis in SPSS. SPSS was then used to screen the data by identifying missing values and outliers in the responses received. Non-response bias and non-normal variables in the data in SPSS were also checked for.

Stage 2: Respondent Profile and Descriptive Statistics

A tabulation of demographic data on respondents was completed in SPSS using descriptive statistics.

Stage 3: Ensuring Research Design and Validity

In SPSS, an Exploratory Factor Analysis (EFA) was implemented. Thereafter, Cronbach's alpha reliability testing of the study's instrument variables (Vanderstoep & Johnson, 2009) was conducted.

Step 4: Hypothesis Testing

SmartPLS was used to test the conceptual model by creating a structural path model. The structural path model was used to test the hypothesised relationships of the study using PLS-SEM. PLS-SEM is most appropriate for research where the researcher's objective is to predict and explain hypothesised relationships between a set of predictors and target constructs (Hair Jr et al., 2017).

3.8.1 *Test for Confounding Effects (Control Variables)*

The demographic variables age, gender, education, and income were included as controls in estimating the structural path model.

In line with previous studies (e.g. Pal et al., 2020), the potential effects of demographic variables such as gender, age, education, and income have been tested as controls for confounding effects on behavioural intentions to adopt, use, or continue using technologies.

The selected demographic controls were found to have no confounding effects.

3.8.2 *Post-Hoc Analysis*

a. *Importance-Performance Map Analysis (IPMA) Test*

To enrich the empirical findings of the study, the researcher took an additional step of applying an enhanced PLS-SEM test.

The Importance-Performance Map Analysis (IPMA) was conducted at the construct-level using PLS-SEM. This test enhances PLS-SEM estimates following estimation of path model relationships, by factoring in average values of the latent variables examined. The IPMA is used to compute and compare the structural path model's total effects (importance) to corresponding latent variable scores (performance) average values of a set of predecessor constructs to determine the most critical areas for managerial or policy-related intervention (action, attention, or improvement).

The aim of this test is to identify those predictors that have relatively high importance for predicting the target construct, with relatively low performance for managerial or policy-related intervention. Predictors with lower importance compared to other constructs are considered of low priority for performance enhancement, as they would have minimal impact in improving the target (criterion) construct.

For the present study, behavioural intention to adopt DFS was the identified target construct.

IPMA results are graphically output to aid visual interpretation (Hair et al., 2018). Total effects denote the importance of predictors, whereas average latent variable scores signify their performance. By comparing corresponding importance and performance scores, the researcher can identify essential areas for managerial or policy-related improvement.

This post-hoc analysis was deemed most useful to the study's context of behavioural intention to adopt DFS among SASSA social grant beneficiaries in South Africa.

3.9 Possible limitations and challenges of the study

The present study had some limitations.

First, the research design was cross-sectional. Thus, the study only focused on respondents at a specific point in time. Therefore, any changes in adoption intention over a prolonged time period among the study's respondents were not observed within the scope of the study. The approach chosen was preferred as it allowed the researcher to measure adoption intention perceptions at an aggregated level. The study was conducted after the COVID-19 pandemic, which would have positively impacted digital payments as governments encouraged digital payment use. This impact provided critical insights previously not evidenced in other DFS adoption studies.

Second, the sample unit identified for this study was social grant holders, likely not the only group using cash. This limitation excluded individuals who are not social grant recipients using cash to transact, whose feedback could shed more light on the cash phenomenon experienced in South Africa and other emerging economies like Nigeria (FIS, 2022). Therefore, the study cannot generalise that KSD Local Municipality's responses represent all communities that use cash for payments.

Thirdly, given the population and context of the present study, respondents may have had to be more literate to understand the questions posed in the study's survey instrument. This limitation may have resulted in their responses containing

flaws or in some instances, inaccurate information. Considering this limitation, the researcher and his assistants were available when the instrument was being implemented for consultation and to clarify any questions posed by the respondents.

3.10 Quality Assurance

3.10.1 *Content Validity and Face Validity*

Face Validity is concerned with measuring the extent to which the construct seems to capture what it should capture (Bhattacherjee, 2012). To test face validity in the present, a pre-test was conducted before the commencement of the main study.

Prior to the pre-testing phase for the study, a pilot study was conducted in the Port St. Johns Local Municipality. In this community, ten (10) social grant holders were surveyed to determine their comfort levels with the proposed instrument for this study. This exercise was useful for the study in ensuring that respondents quickly understood the questionnaire and any discrepancies that must be addressed before the primary data collection stage. Responses obtained from the pilot study also provided a preliminary indication of response patterns in preparation for the main data collection phase.

Content Validity is an organised review of the research instrument (Hair et al., 1998). This review will assist in the study by determining whether the instrument captures the content domain of each construct. This review was conducted by obtaining feedback from four candidates during the pre-testing phase. The pre-testers for the study comprised (1) a fellow WBS master's candidate also currently conducting research based in the Financial Services industry and working as a senior manager, (2) a postgraduate researcher working in the field of Development Economics from the University of Western Cape, (3) an experienced Development Economics and Finance expert and consultant who has worked with similar population groups and is a graduate of Rhodes University and Stellenbosch University, respectively.

3.10.2 *Construct Validity*

The measures for the present study were adapted using validated scales from the existing literature where similar studies were conducted. Adjusting these scales decreases the chances of cross-loading and poor construct validity (Pallant, 2007). In the study, variables were merged into a reduced subset. This process required the Principal Component Factor Analysis (PCFA) (Abdi & Williams, 2010). Exploratory Factor analysis (EFA) was used to explore and determine the underlying dimensional factors for constructs.

3.10.3 *Convergent and Discriminant Validity*

Convergent Validity is the degree to which two constructs should be related. To determine convergent validity in this study, constructs were identified from existing literature and were tested and measured to determine whether they are related to adoption intention behaviour. The study used the Average Variance Extracted (AVE) to calculate this validity. The AVE calculation is used to measure constructs and can be defined as measuring the variance captured by a construct in relation to the amount of variance due to measurement error (dos Santos, 2021; Fornell & Larker, 1981).

3.10.4 *Reliability*

The Cronbach's Alpha coefficient was used to test the instrument's reliability (see Section 4.3.3) and will also be used to test the reliability of the data collected in the study. The coefficient does not contain a lower limit. Therefore, the closer to 1 this value is, the stronger the reliability will be for the data (Gliem & Gliem, 2003). This model is the most widely used reliability measurement in social science research. Although this research focuses on technology adoption (Bonett & Wright, 2015), the factors that impact the social sciences as human behaviour when introduced to mobile technology was under investigation in the present study.

3.11 Ethical considerations

Research Ethics has become a critical issue in technology adoption research, with significant progress made following the advent of Artificial Intelligence (AI) (Duan et al., 2020). Therefore, it was essential for this study that ethical considerations were considered. Before collecting data from respondents, the researcher obtained ethical clearance for the present study from the University of the Witwatersrand (Wits) Ethical Committee (see Appendix D). To conduct the study, the researcher also ensured that respondents were anonymous and that data were kept confidential (Terre Blanche et al., 2008). Respondents were asked to voluntarily participate in the study as there would be no financial benefit or incentive provided to them. The researcher and accompanying assistants on location answered any enquiries about the survey to provide the concerned respondents with context and reassurance when participating in the study. The respondents' participation was taken as their consent to participate in the study's survey. Any information shared within the study was not communicated or sent to a third party. Lastly, the study was entirely academic, and the researcher did not make any money from this research.

CHAPTER 4. DATA ANALYSIS AND PRESENTATION OF RESULTS

4.1 Introduction

The research methodology selected for this study is documented in Chapter 3. This chapter will detail the analysis conducted on the collected data. First, screening procedures and sample demographics will be discussed. Second, the reliability and validity tests with descriptive statistics and factor analysis will be discussed. Next, the correlation between the independent and dependent variables will be discussed. Thereafter, results following tests of the hypothesis proposed in Chapter 2 will be presented and discussed. Finally, the chapter will be summarised.

4.2 Data Screening

4.2.1 *Response Rate*

A structured questionnaire developed for the study was distributed to 218 respondents, from which 215 acceptable responses were received, resulting in a response rate of 98.6%, as shown in Table 5.

Distributed Questionnaire	Responses	Response Rate
218	215	98.6%

Table 5: Response Rate

Three questionnaires needed to be completed were returned and thus excluded from the present study. The data collected through the use of paper-based questionnaires were first captured using Microsoft Excel and then imported to IBM SPSS (Version 28) for data preparation and analysis. The data were prepared in a number of phases. First, the data were screened for missing values and examined for outliers. Second,

the data were analysed for normality, which is an essential assumption for multivariate data analysis (Hair et al., 2010).

4.2.2 *Demographic Profile of Respondents*

A demographic profile was obtained from the data set to determine emergent patterns among the SASSA grant respondents. Table 6 illustrates the study's respondent profile (n = 215).

Age (n = 215)		
Demographic Variable	**Frequency**	**Percentage**
Below 20 years	13	6.0%
21 – 30 years	47	21.9%
31 – 40 years	59	27.4%
41 – 50 years	30	14%
51 – 60 years	27	12.6%
Above 60 years	32	14.9%
Prefer not to say	7	3.3%
Gender (n = 215)		
Demographic Variable	**Frequency**	**Percentage**
Male	60	27.9%
Female	147	68.4%
Prefer not to say	8	3.7%
Marital Status (n = 215)		

Demographic Variable	Frequency	Percentage
Single/Never Married	92	42.8%
Married/Living Together	76	35.3%
Divorced/Separate	19	8.8%
Widowed	19	8.8%
Prefer not to say	5	2.3%
Missing Data	4	1.9%
Family Size (n = 215)		
Demographic Variable	**Frequency**	**Percentage**
None	28	13.0%
1 – 2 Children	76	35.3%
3 – 4 Children	73	34.0%
5 or more children	35	16.3%
Missing Data	3	1.4%
Education Level (n = 215)		
Demographic Variable	**Frequency**	**Percentage**
Primary School (Basic)	52	24.2%
High School (Matric)	86	40.0%
Diploma	21	9.8%
No Formal Education	47	21.9%
Other	8	3.7%

Missing Data	1	0.5%
Annual Income (n = 215)		
Demographic Variable	**Frequency**	**Percentage**
Less than R 10 000	49	22.8%
R 10 000 – 30 000	53	24.7%
R 30 000 – 54 000	10	4.7%
R 54 000 and above	9	4.2%
No Income	82	38.1%
Missing Data	5	2.3%
Employment Status Level (n = 215)		
Demographic Variable	**Frequency**	**Percentage**
Full-Time Employee	17	7.9%
Part-Time Employee	39	18.1%
Unemployed	150	69.8%
Other	3	1.4%
Missing Data	6	2.8%

Table 6: Demographic Frequency Distribution

Seven demographic variables were assessed to profile the respondents. These demographic variables included Age, Gender, Marital Status, Family Size, Education Level, Annual Income, and Employment Status, as individual characteristics of the study's respondents.

Most of the respondents were female (68.4%), with males representing 27.9% of the population sampled. Further, most respondents were aged 31-40 years (27.4%), followed by those aged 21-30 years (21.9%). Further, more respondents reported that they were Single/Never Married (42.8%), followed by those Married/Living Together (35.3%). The family size dynamic showed that most respondents have 1–2 children (35.3%), followed by those with 3–4 children (34%), with the two categories comprising nearly 70% of the sampled population.

The demographic variables Education Level, Annual Income, and Employment Status were also observed. Analysis of the Education Level variable showed that most respondents reported that they were educated up to High School (Matric) (40%), followed by those who only studied up to Primary School (Basic) (24.2%). In terms of annual income, most respondents reported No Income (38.2%), followed by those who reported R 10,000–R 30,000 (24.7%). Lastly, in terms of Employment Status, the majority of respondents reported that they were Unemployed (69.8%), followed by those who reported as Part-Time Employee (18.9%).

4.2.3 *Missing Value Analysis*

“Missing Data is the number of cases with missing data per variable and the number of variables with missing data per case” (Hair et al., 2010). The study found missing data from demographic, predictor, and criterion variables at a case level. The mean substitution method was used to replace missing values with the series mean for the variable across the data set. This method allows the study to hold sample size and confirm that all cases had complete data (Hair et al., 2010). Table 7 shows the cases and variables that contained missing data.

Although this method was used, 5 cases where the missing value exceeded 10% (greater than 3) for predictor and criterion variables (Hair et al., 2010), were identified. This resulted in cases 8, 66, 86, 186, and 212 being excluded from the study. Therefore, the sample population retained for subsequent analyses was 210 (n = 210).

Missing Data			
Variable	**Measurement Item**	**Number of Missing Values**	**Replaced with Series Mean**
Performance Efficiencies	PE1_1	2	Yes
	PE2_1	0	No
	PE3_1	1	Yes
	PE4_1	0	No
Effort Efficiencies	EE1_1	0	No
	EE2_1	4	Yes
	EE3_1	2	Yes
	EE4_1	0	No
Network Externalities	NE1_1	1	Yes
	NE2_1	0	No
	NE3_1	0	No
Facilitating Conditions	FC1_1	2	Yes
	FC2_1	2	Yes
	FC3_1	2	Yes
	FC4_1	0	No
Perceived Value	PV1_1	0	No
	PV2_1	0	No
	PV3_1	1	Yes

Trust	T1_1	1	Yes
	T2_1	1	Yes
	T3_1	2	Yes
	T4_1	0	No
Price Benefit	PB1_1	0	No
	PB2_1	0	No
	PB3_1	0	No
Perceived Cost	PC1_1	2	Yes
	PC2_1	0	No
	PC3_1	1	Yes
Unavailability of Facilitating Conditions	UFC1_1	0	No
	UFC2_1	0	No
	UFC3_1	0	No
Perceived Risk	PR1_1	0	No
	PR2_1	0	No
	PR3_1	0	No
	PR4_1	0	No
Behavioural Intention	BI1_1	1	Yes
	BI2_1	0	No
	BI3_1	0	No

Table 7: Missing Values SPSS Output

4.2.4 *Outliers*

The univariate method compares one variable at a time, whereas the multivariate method compares multiple variables with each other (Hair et al., 2010). An outlier can cause doubt in a study as it is an observation which deviates from other observations in a data set (Zulkipli & Rambli, 2019). Although this is a multivariate study due to the various predictor and criterion variables, the univariate method was used for outlier detection analysis, allowing each variable to be analysed to determine outliers. Since the sample study comprised 210 respondents (n = 210), individual variable responses were standardised and analysed to ensure that the standardised scores were less than +4 and -4 respectively, for large sample sizes (Hair et al., 2010). The threshold of +4 and -4 is used to determine unusually high or low values of extreme response patterns (Hair et al., 2010). The study found that all the responses were within the stipulated threshold. Thus, no outliers were identified in the study.

4.2.5 *Normality*

Descriptive Statistics						
Variable	**Dimension**	**Number of Missing Values**	**Replaced with Series Mean**	**Standard Deviation**	**Skewness**	**Kurtosis**
Performance Efficiencies	PE1_1	2	Yes	0.99427	-0.553	-0.628
	PE2_1	0	No	1.06376	-0.313	-0.855
	PE3_1	1	Yes	1.11003	-0.027	-1.150
	PE4_1	0	No	1.19528	0.041	-1.264
Effort Efficiencies	EE1_1	0	No	1.10778	-0.240	-0.971
	EE2_1	4	Yes	1.14386	-0.223	-1.120
	EE3_1	2	Yes	1.19870	-0.363	-0.910
	EE4_1	0	No	1.17997	-0.279	-0.985
	NE1_1	1	Yes	1.10889	0.095	-1.267

Network Externalities	NE2_1	0	No	1.15273	0.283	-1.138
	NE3_1	0	No	1.08387	0.308	-1.119
Facilitating Conditions	FC1_1	2	Yes	1.12977	0.127	-1.175
	FC2_1	2	Yes	1.29108	-0.228	-1.245
	FC3_1	2	Yes	1.12798	-0.176	-1.047
	FC4_1	0	No	0.99327	-0.471	-0.628
Perceived Value	PV1_1	0	No	1.03895	-0.203	-1.213
	PV2_1	0	No	1.10622	-0.032	-1.227
	PV3_1	1	Yes	1.15181	-0.142	-1.114
Trust	T1_1	1	Yes	1.23991	0.039	-1.269
	T2_1	1	Yes	1.35255	-0.143	-1.240
	T3_1	2	Yes	1.47010	0.094	-1.435
	T4_1	0	No	1.35161	-0.007	-1.313

Price Benefit	PB1_1	0	No	1.16610	0.450	-0.926
	PB2_1	0	No	1.13244	0.436	-0.820
	PB3_1	0	No	1.23613	0.446	-0.854
Unavailability of Facilitating Conditions	UFC1_1	0	No	1.29592	-0.276	-1.236
	UFC2_1	0	No	1.33860	-0.215	-1.249
	UFC3_1	0	No	1.39335	-0.522	-1.077
Perceived Risk	PR1_1	0	No	1.30674	-0.434	-1.040
	PR2_1	0	No	1.23502	-0.085	-1.370
	PR3_1	0	No	1.24980	-0.238	-1.206
	PR4_1	0	No	1.29689	-0.017	-1.356
Perceived Cost	PC1_1	2	Yes	1.05515	0.064	-0.890
	PC2_1	0	No	1.07522	0.094	-0.930
	PC3_1	1	Yes	1.11316	-0.005	-0.793

Behavioural Intention	BI1_1	1	Yes	1.20508	-0.648	-0.732
	BI2_1	0	No	1.31112	-0.395	-1.193
	BI3_1	0	No	1.24033	-0.671	-0.618

Table 8: Descriptive Statistics (with Skewness and Kurtosis)

Table 8 displays the descriptive statistics for the predictor and criterion variables. According to Hair et al. (2010) normality is an essential assumption of multivariate analysis. It refers to data distribution per individual metric variable and its correspondence to the normal distribution. The values for skewness were between -2 and +2, and for Kurtosis, between -3 and +3, respectively, indicating that the variables were appropriate (Hair et al., 2010).

4.3 Preparation for Factor Analysis

4.3.1 *Factorability*

According to Hair et al. (2010), all the independent variables should be inter-correlated to evaluate suitability when assessing the construct dimensions for factor analysis. The study followed this method to determine factorability. Factorability determines whether the study's variables are adequate for Factor Analysis. To determine Factorability, each of the variable's dimensions were inter-correlated with the independent variable, where the score is greater than 0.300. An inter-correlation score of less than 0.300 indicates that factorability is diminished. The item should be included before factor analysis (Hair et al., 2010).

Performance Expectancy, in terms of factorability of dimensions PE1, PE2, PE3 and PE4, inter-correlated with values greater than 0.300. Therefore, this factor and its dimensions were retained. Effort Expectancy inter-correlated with dimensions EE1, EE2, EE3, and EE4, with values greater than 0.300. These dimensions were also retained. Network Externalities inter-correlated with dimensions NE1, NE2 and NE3 with values greater than 0.300. This factor and its dimensions were retained.

For Facilitating Conditions, not all the dimensions (FC1, FC2, FC3) inter-correlated with a value greater than 0.300. Further analysis of communality scores identified that dimension FC2 was the lowest score where it was observed that FC2 was not correlating well with FC1, FC3, and FC4. Therefore, FC2 was discarded after reviewing its definition and operation. As such, from the defined variables in Chapter 2, only FC1, FC3, and FC4 were retained. Perceived Value inter-correlated with PV1, PV2, and PV3, with values greater than 0.300, and these dimensions were retained.

Trust was inter-correlated with dimensions T1, T2, T3, and T4, with a score greater than 0.300. Therefore, these dimensions were also retained. Price Benefit inter-correlated with PB1, PB2, and PB3, with a score greater than 0.300. Thus, these dimensions were retained. Unavailability of Facilitating Conditions inter-correlated with UFC1, UFC2, and UFC3, with a score greater than 0.300. Therefore, these dimensions were also retained. Perceived Risk was also inter-correlated with dimensions PR1, PR2, PR3, and PR4, with values greater than 0.300. Consequently, these dimensions were retained.

For Perceived Costs, not all dimensions inter-correlated with a value greater than 0.300. PC1 was not correlating well with PC2 and PC3, as the scores were below the required threshold. This poor inter-correlation coupled with a low communality score of 0.343, well below 0.500, as well as a review of the variable's definition and its operationalisation in Chapter 3, resulted in PC1 being discarded. The dimensions PC2 and PC3 inter-correlated with values greater than 0.300. Thus, these were the variable dimensions that were retained.

4.3.2 *Exploratory Factor Analysis (EFA)*

Principle Component Factor Analysis (PCFA) with Promax orthogonal rotation, where Kaiser normalisation was included, was used for factor analysis. Factors were interpreted as follows (Hair et al., 2010):

1. Items must have high loadings on a single factor.
2. Unless theoretically proven, factors that load on two or more factors are deleted.
3. Variables with 0.5 or more commonalities will be retained for further analysis.

Table 9 details the dimensions excluded from the study based on the above recommendations from (Hair et al., 2010).

Items Excluded after PCFA				
Variable	**Number of Initial Dimensions**	**Number of Retained Dimensions**	**Dimension excluded**	**Rationale**
Facilitating Conditions	4	3	FC2	Inclusion reduces the factorability of data
Perceived Cost	3	2	PC1	Inclusion reduces the factorability of data

Table 9: Dimensions Excluded after PCFA

EFA requires extraction and rotation approaches to determine the one-dimensionality of each variable. Extraction was used to summarise the information within variables into fewer dimensions with minimal lost data. Rotation assists in reallocating the factor variance to obtain a more meaningful theoretical configuration. PCA extraction with Promax (Oblique) Rotation was the selected method. To determine the factor loadings' practical significance, factor loadings must be evaluated against the following conditions:

1. Dimensions should have high loadings above 0.300.
2. Dimensions that have loadings on two or more factors are ruled out, baring theoretical justification (Hair et al., 2010).
3. Dimensions should exceed a communality score of 0.500 (Hair et al., 2010).

Further, the Bartlett's Test of Sphericity and Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy were used.

The optimal solution for the dimensions of Performance Expectancy is presented in Table 10:

Principal Component Analysis (PCA) Result: Performance Expectancy	
Dimension	**Factor**
	1
SMEAN(PE1)	0.890
SMEAN(PE2)	0.908
SMEAN(PE3)	0.903
SMEAN(PE4)	0.931

Table 10: Principal Component Analysis (PCA) Result: Performance Expectancy

To achieve the optimal solution for Performance Expectancy, a single run was required as it resulted in high communality scores. It was determined that Performance Expectancy is represented by PE1, PE2, PE3, and PE4, which had the highest factor loadings and explained 82% of the variance.

Total Variance Explained: Performance Expectancy						
	Initial Eigenvalues			**Extraction Sum of Squared Loadings**		
Component	**Total**	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
1	3.301	82.529	82.529	3.301	82.529	82.529
2	0.286	7.157	89.686			
3	0.268	6.695	96.382			

4	0.145	3.618	100.000			
Extraction Method: Principal Component Analysis						

Table 11: Total Variance Explained: Performance Expectancy

The dimensions of Performance Expectancy comprised four dimensions. Factor 1 had an Eigen value of 3.301 (> 1), explaining 82.53% of the variance.

The optimal solution for the dimensions of Effort Expectancy is presented in Table 12:

Principal Component Analysis (PCA) Result: Effort Expectancy	
Dimension	**Factor**
	1
SMEAN(EE1)	0.946
SMEAN(EE2)	0.960
SMEAN(EE3)	0.959
SMEAN(EE4)	0.946

Table 12: Principal Component Analysis (PCA) Result: Effort Expectancy

The optimal solution for Effort Expectancy is represented by EE1, EE2, EE3, and EE4 as they had the highest communality scores and factor loadings and explained 90.72% of the variance.

Total Variance Explained: Effort Expectancy						
	Initial Eigenvalues			**Extraction Sum of Squared Loadings**		
Component	**Total**	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**

1	3.630	90.762	90.762	3.630	90.762	90.762
2	0.169	4.219	94.981			
3	0.108	2.711	97.692			
4	0.092	2.308	100.000			
Extraction Method: Principal Component Analysis						

Table 13: Total Variance Explained: Effort Expectancy

The dimensions of Effort Expectancy comprised 4 components. Factor 1 had an Eigen value of 3.360 (> 1), explaining 90.76% of the variance. The optimal solution for the dimensions of Network Externalities is presented in Table 14.

Principal Component Analysis (PCA) Result: Network Externalities	
Dimension	**Factor**
	1
SMEAN(NE1)	0.931
SMEAN(NE2)	0.950
SMEAN(NE3)	0.917

Table 14: Principal Component Analysis (PCA) Result: Network Externalities

NE1, NE2, and NE3 represent the optimal solution for Network Externalities as they had the highest communality scores and factor loadings and explained 87.04% of the variance.

Total Variance Explained: Network Externalities		
Component	**Initial Eigenvalues**	**Extraction Sum of Squared Loadings**

	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.611	87.041	87.041	2.611	87.041	87.041
2	0.245	8.152	95.193			
3	0.144	4.807	100.000			
Extraction Method: Principal Component Analysis						

Table 15: Total Variance Explained: Network Externalities

The dimensions of Network Externalities comprised 3 components. Factor 1 had an Eigen value of 2.611 (> 1), explaining 87.04% of the variance. The optimal solution for the dimensions of Facilitating Conditions is presented in Table 16.

Principal Component Analysis (PCA) Result: Facilitating Conditions	
Dimension	**Factor**
	1
SMEAN(FC1)	0.603
SMEAN(FC3)	0.753
SMEAN(FC4)	0.702

Table 16: Principal Component Analysis (PCA) Result: Facilitating Conditions

Multiple runs were required to achieve an optimal solution for Facilitating Conditions for which a low communality score for the dimension FC2 was initially obtained. Through analysis and elimination, it was determined that Facilitating Conditions is optimally represented by FC1, FC3, and FC4, which had the highest factor loadings and explained 87.04% of the variance.

Total Variance Explained: Facilitating Conditions						
Component	Initial Eigenvalues			Extraction Sum of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.611	87.041	87.041	2.611	87.041	87.041
2	0.245	8.152	95.193			
3	0.144	4.807	100.000			
Extraction Method: Principal Component Analysis						

Table 17: Total Variance Explained: Facilitating Conditions

The dimensions of Facilitating Conditions comprised three components. Factor 1 had an Eigen value of 2.611 (> 1), explaining 87.04% of the variance. The optimal solution for the dimensions of Perceived Value is presented in Table 18.

Principal Component Analysis (PCA) Result: Perceived Value	
Dimension	Factor
	1
SMEAN(PV1)	0.926
SMEAN(PV3)	0.943
SMEAN(PV3)	0.867

Table 18: Principal Component Analysis (PCA) Result: Perceived Value

PV1, PV2, and PV3 represent the optimal solution for Perceived Value as they had the highest communality scores and factor loadings and explained 83.34% of the variance.

Total Variance Explained: Perceived Value						
Component	Initial Eigenvalues			Extraction Sum of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.500	83.336	83.336	2.500	83.336	83.336
2	0.358	11.931	95.267			
3	0.142	4.733	100.000			

Table 19: Total Variance Explained: Perceived Value

The dimensions of Perceived Value comprised three components. Factor 1 had an eigenvalue of 2.500 (> 1), explaining 83.34% of the variance. The optimal solution for the dimensions of Trust is presented in Table 20.

Principal Component Analysis (PCA) Result: Trust	
Dimension	Factor
	1
SMEAN(T1)	0.875
SMEAN(T3)	0.877
SMEAN(T3)	0.895
SMEAN(T4)	0.883

Table 20: Principal Component Analysis (PCA) Result: Trust

T1, T2, T3, and T4 represent the optimal solution for Trust as they had the highest communality scores and factor loadings and explained 88.24% of the variance.

Total Variance Explained: Trust						
Component	Initial Eigenvalues			Extraction Sum of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.529	88.236	88.236	3.529	88.236	88.236
2	0.179	4.485	92.721			
3	0.166	4.161	96.882			
4	0.125	3.118	100.000			
Extraction Method: Principal Component Analysis						

Table 21: Total Variance Explained: Trust

The dimensions of Trust comprise four components. Factor 1 had an Eigen value of 3.529 (> 1), explaining 88.24% of the variance. The optimal solution for the dimensions of Price Benefit is presented in Table 22.

Principal Component Analysis (PCA) Result: Price Benefit	
Dimension	Factor
	1
SMEAN(PB1)	0.925
SMEAN(PB2)	0.949
SMEAN(PB3)	0.920

Table 22: Principal Component Analysis (PCA) Result: Price Benefit

PB1, PB2, and PB3 represent the optimal solution for Price Benefit as they had the highest communality scores and factor loadings and explained 86.79% of the variance.

Total Variance Explained: Price Benefit						
	Initial Eigenvalues			Extraction Sum of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.604	86.786	86.786	2.604	86.786	86.786
2	0.246	8.210	94.996			
3	0.150	5.004	100.000			
Extraction Method: Principal Component Analysis						

Table 23: Total Variance Explained: Price Benefit

The dimensions of Price Benefit comprised three components. Factor 1 had an Eigen. value of 3.529 (> 1), explaining 86.79% of the variance. The optimal solution for the dimensions of Perceived Risk is presented in Table 24.

Principal Component Analysis (PCA) Result: Perceived Risk	
Dimension	Factor
	1
SMEAN(PR1)	0.913
SMEAN(PR3)	0.940
SMEAN(PR3)	0.946
SMEAN(PR4)	0.946

Table 24: Principal Component Analysis (PCA) Result: Perceived Risk

PR1, PR2, PR3, and PR4, represent the optimal solution for Perceived Risk as they had the highest communality scores and factor loadings, and explained 87.68% of the variance.

Total Variance Explained: Perceived Risk						
	Initial Eigenvalues			Extraction Sum of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.507	87.679	87.679	3.507	87.679	87.679
2	0.239	5.982	93.661			
3	0.155	3.874	97.534			
4	0.099	2.466	100.000			
Extraction Method: Principal Component Analysis						

Table 25: Total Variance Explained: Perceived Risk

The dimensions of Perceived Risk comprised four components. Factor 1 had an Eigen. value of 3.507 (> 1), explaining 87.68% of the variance. The optimal solution for the dimensions of Unavailability Facilitating Conditions is presented in Table 26:

Principal Component Analysis (PCA) Result: Unavailability of Facilitating Conditions	
Dimension	Factor
	1
SMEAN(UFC1)	0.918

SMEAN(UFC2)	0.940
SMEAN(UFC3)	0.913

Table 26: Principal Component Analysis (PCA) Result: Unavailability of Facilitating Conditions

UFC1, UFC2, and UFC3 represent the optimal solution for Unavailability of Facilitating Conditions as they had the highest communality scores and factor loadings and explained 85.33% of the variance.

Total Variance Explained: Unavailability of Facilitating Conditions						
Component	**Initial Eigenvalues**			**Extraction Sum of Squared Loadings**		
	Total	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
1	2.560	85.331	85.331	2.560	85.331	85.331
2	0.262	8.738	94.068			
3	0.178	5.932	100.000			
Extraction Method: Principal Component Analysis						

Table 27: Total Variance Explained: Unavailability of Facilitating Conditions

The dimensions of Unavailability of Facilitating Conditions comprised three components. Factor 1 had an Eigenvalue of 2.560 (> 1), explaining 85.33% of the variance. The optimal solution for the dimensions of Perceived Cost is presented in Table 28.

Principal Component Analysis (PCA) Result: Perceived Cost	
Dimension	**Factor**
	1
SMEAN(PC2)	0.914
SMEAN(PC3)	0.914

Table 28: Principal Component Analysis (PCA) Result: Perceived Cost

Multiple runs were required to achieve the optimal solution for Perceived Cost as the initial result in a low communality score for the dimension PC1. Through analysis and elimination, it was determined that Perceived Cost is optimally represented by PC2 and PC4, which had the highest factor loadings and explained 83.48% of the variance.

Total Variance Explained: Perceived Cost						
	Initial Eigenvalues			**Extraction Sum of Squared Loadings**		
Component	**Total**	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
1	1.670	83.480	83.480	1.670	83.480	83.480
2	0.330	16.520	100.00			
Extraction Method: Principal Component Analysis						

Table 29: Total Variance Explained: Perceived Cost

The dimensions of Perceived Cost comprised two dimensions. Factor 1 had an eigenvalue of 1.670 (> 1), explaining 83.48% of the variance.

4.3.3 *Reliability*

The study applied the Cronbach's Coefficient Alpha Value to examine the consistency and reliability of the revised scales. A threshold of 0.700 is considered appropriate for items deemed reliable (Nunnally, 1978) and retained for further study. The study's results revealed the factors to be reliable and thus were retained. Table 30 below details the output from the reliability tests:

Table 30: Instrument (Construct) Reliabilities

Variable	Dimension Items	No. of Items	Cronbach's Alpha
Performance Expectancy	PE1	4	0.928
	PE2		
	PE3		
	PE4		
Effort Expectancy	EE1	4	0.966
	EE2		
	EE3		
	EE4		
Network Externalities	NE1	3	0.925
	NE2		
	NE3		
Facilitating Conditions	FC1	3	0.767
	FC3		
	FC4		

Perceived Value	PV1	3	0.897
	PV2		
	PV3		
Trust	T1	4	0.954
	T2		
	T3		
	T4		
Price Benefit	PB1	3	0.923
	PB2		
	PB3		
Perceived Risk	PR1	4	0.953
	PR2		
	PR3		
	PR4		
Unavailability of Facilitating Conditions	UFC1	3	0.914
	UFC2		
	UFC3		
Perceived Cost	PC2	2	0.802
	PC3		

Table 30: Instrument (Construct) Reliabilities

4.3.4 *Descriptive Statistics for Composites*

Variable	N Statistic	Mean	Standard Deviation	Skewness	Kurtosis
Performance Expectancy	210	3.4161	0.99196	-0.100	-0.912
Effort Expectancy	210	3.2145	1.10289	-0.278	-1.123
Network Externalities	210	2.8603	1.04068	0.276	-1.197
Facilitating Conditions	210	3.2913	0.89679	-0.009	-0.763
Perceived Value	210	3.1589	1.00199	-0.083	-1.185
Trust	210	3.1313	1.27182	0.086	-1.243
Price Benefit	210	2.8683	1.09714	0.510	-0.711
Perceived Risk	210	3.2631	1.24897	-0.441	-0.956
Unavailability of Facilitating Conditions	210	2.9873	1.16426	-0.163	-1.178
Perceived Cosy	210	3.1099	0.99976	0.125	-0.471
Behavioural Intention	210	3.7060	1.19456	-0.513	-0.832

Table 31: Descriptive Statistics for Composites

Table 31 above details the descriptive statistics for the composite scores. The standard deviation scores are close to 1, indicating response consistency (Hair et al., 2010). The Skewness scores for composites were between the acceptable range of -

2.000 to +2.000, and for Kurtosis range from -3.000 to +3.000. The variables were, thus, acceptable (Hair et al., 2010).

4.3.5 *Pearson's Test of Correlation*

	PEC	EEC	NEC	FCC	PVC	TC	PBC	PRC	UFCC	PCC	BIC
PEC	1	0.446	0.486	0.589	0.729	0.365	0.376	-0.452	-0.371	0.229	0.524
EEC	0.446	1	0.648	0.589	0.338	0.603	0.496	-0.644	-0.676	0.495	0.209
NEC	0.486	0.648	1	0.454	0.538	0.509	0.544	0.596	0.622	0.451	0.399
FCC	0.589	0.589	0.454	1	0.671	0.643	0.566	-0.552	-0.527	0.503	0.622
PVC	0.729	0.338	0.538	0.400	1	0.428	0.423	-0.377	-0.394	0.283	0.646
TC	0.365	0.603	0.509	0.643	0.428	1	0.675	-0.763	-0.589	0.645	0.477
PBC	0.376	0.496	0.544	0.566	0.423	0.675	1	-0.692	-0.581	0.607	0.530
PRC	-0.452	-0.644	-0.596	-0.552	-0.377	-0.763	-0.692	1	0.653	-0.551	-0.429
UFCC	-0.371	-0.676	-0.622	-0.527	-0.394	-0.589	-0.581	0.653	1	-0.525	-0.320
PCC	0.229	0.495	0.451	0.503	0.283	0.645	0.607	-0.551	-0.525	1	0.303
BIC	0.524	0.209	0.399	0.622	0.646	0.477	0.530	-0.429	-0.320	0.303	1

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

Table 32: Pearson's Test of Correlation Outcome

Table 32 details the output of Pearson's Test of Correlation for the Composites. Pearson's Test of Correlation highlights significant inter-correlations between variables.

Since Pearson's correlation test is insufficient for testing the variable inter-correlations, the present study lends itself to the more robust structural equation modelling (SEM) (Hair Jr et al., 2017). Therefore, the testing of a structural path model was utilised as the preferred method to evaluate the study's hypothesised relationships proposed in Chapter 2.

4.4 Evaluation of Structural Path Model

This section involves assessing the model's predictive capacity in testing the hypothesised relationships proposed in the conceptual model of the study (Hair Jr et al., 2017). The structural path model is assessed after a successful evaluation of the validity and reliability of the measures of the constructs were established.

4.4.1 *Collinearity Testing*

Collinearity testing is crucial because the estimation of path coefficients for dependent variables should not be affected by levels of substantial collinearity across predictor (construct) variables. Table 33 details the results of the test for collinearity.

Criterion: Behavioural Intention to Adopt Digital Financial Services (DFS)		
Predictor	**Tolerance**	**VIF**
Perceived Effectiveness	0.401	2.494
Effort Expectancy	0.409	2.443
Facilitating Conditions	0.611	1.638

Network Externalities	0.400	2.503
Price Benefit	0.399	2.505
Perceived Value	0.380	2.629
Trust	0.424	2.361
Unavailability of Facilitating Conditions	0.417	2.396
Perceived Risk	0.333	3.003
Perceived Cost	0.659	1.518

Table 33: Results of Test for Collinearity

Acceptable thresholds of Tolerance and VIF values were found. Tolerance and VIF values greater than 0.200 and 5.000 respectively, were found (Hair Jr et al., 2014). Collinearity between predictor (construct) variables in the path model was, therefore, not a problem in this investigation.

4.4.2 *Estimation of the Structural Path Coefficients*

The effects of predictors represented by Performance Expectancy, Effort Expectancy, Network Externalities, Price Benefit, Perceived Value, Trust, Unavailability of Facilitating Conditions, Perceived Risk, and Perceived Cost, on the Behavioural Intention to Adopt DFS in the context of South Africa, were assessed using a structural path model. The relative strength of the paths in the structural path model was determined by assessing their coefficients. A non-parametric bootstrapping technique was used to empirically test whether the structural model path coefficients of the hypothesized correlations were significant (Hair Jr et al., 2014). Using this method, a standard error was obtained to estimate the significance of path coefficients. The path coefficients of the structural model were then evaluated for significance using *t* and *p* values (Hair Jr et al., 2014). This study determined that a value of 1.96 for a significance level of 5% was used to interpret statistical significance levels for critical *t* values. According to Hair Jr. et al. (2017), the bootstrapped confidence intervals

specifies the range within which the true population parameter lies under the assumption of a given confidence level by using standard errors from bootstrapping (Hair Jr et al., 2017). Therefore, bootstrapped confidence intervals were obtained using the Bias-Corrected and Accelerated technique to enhance information on the stability of the calculated coefficients. To determine whether the path coefficients significantly deviated from zero, a bootstrap confidence interval of 95% was utilised (Hair Jr et al., 2017). It was noted that the confidence intervals for a calculated path coefficient that excluded zero had a substantial impact, whereas those that included zero had no impact.

Figure 6 shows the structural path model that was estimated to test the relationship between Behavioural Intention to Adopt DFS and its predictors Performance Expectancy, Effort Expectancy, Network Externalities, Facilitating Conditions, Perceived Value, Price Benefit, Perceived Risk, Unavailability of Facilitating Conditions, and Perceived Cost.

4.4.3 *Structural Path Model*

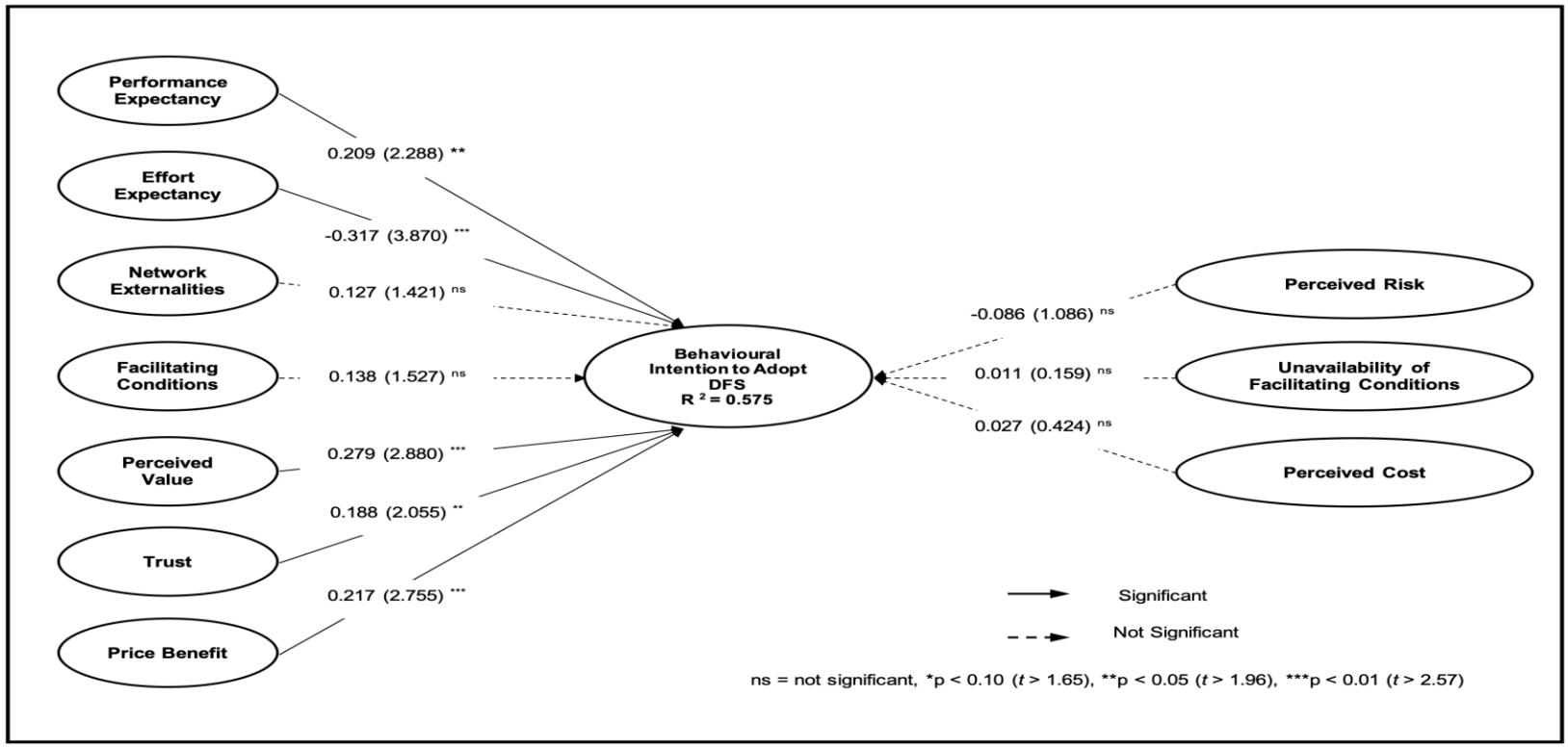

Figure 7: Structural Path Model (n = 210)

Control Variables
Age → Behavioural Intention to Adopt DFS (path coefficient = 0.078, *t* = 1.331, p < 0.10)
Gender → Behavioural Intention to Adopt DFS (path coefficient = -0.033, *t* = 0.684, p < 0.10)
Education → Behavioural Intention to Adopt DFS (path coefficient = -0.079, *t* = 1.589, p < 0.10)
Income → Behavioural Intention to Adopt DFS (path coefficient = 0.004, *t* = 0.066, p < 0.10)
Note: For schematic clarity, the observed non-significant (ns) effects of control variables on the dependent variable Behavioural Intention to Adopt DFS, are not drawn.

Significance Testing of the Structural Path Model Coefficients					
Path	**Path Coefficient**	**t value**	**p value**	**Sig. Level**	**95% CI**
Performance Expectancy→ Behavioural Intention to Adopt DFS	0.209	2.288	0.022	**	[-0.015, 0.346]
Effort Expectancy→ Behavioural Intention to Adopt DFS	-0.317	3.870	0.000	***	[-0.460, -0.140]
Network Externalities→ Behavioural Intention to Adopt DFS	0.127	1.421	0.155	ns	[-0.069, 0.288]
Facilitating Conditions→ Behavioural Intention to Adopt DFS	0.138	1.527	0.127	ns	[0.016, 0.400]
Price Benefit→ Behavioural Intention to Adopt DFS	0.217	2.755	0.006	***	[0.069, 0.378]
Perceived Risk→ Behavioural Intention to Adopt DFS	-0.086	1.086	0.278	ns	[-0.224, 0.089]
Trust→ Behavioural Intention to Adopt DFS	0.188	2.055	0.040	**	[0.007, 0.372]
Unavailability of Facilitating Conditions→	0.011	0.159	0.874	ns	[-0.121, 0.165]

Behavioural Intention to Adopt DFS					
Perceived Value→ Behavioural Intention to Adopt DFS	0.279	2.880	0.004	***	[0.120; 0.496]
Perceived Cost→ Behavioural Intention to Adopt DFS	0.027	0.424	0.671	ns	[-0.074, 0.182]

ns = not significant, *p < 0.10 (t > 1.65), **p < 0.05 (t > 1.96), ***p < 0.01 (t > 2.57)

Table 34: Significance Testing of the Structural Path Model Coefficients

The results following significance testing of hypothesised relationships (Table 34) indicate that Performance Expectancy had a significant and positive relationship with Behavioural Intention to Adopt DFS (path coefficient = 0.209, t = 2.288, p < 0.01). There was no absolute zero value, as indicated by the bootstrapping confidence interval. Effort Expectancy had a significant and negative relationship with Behavioural Intention to Adopt DFS (path coefficient = -0.317, t = 3.870, p<0.01). There was no absolute zero value, as indicated by the bootstrapping confidence interval. Network Externalities was shown not to significantly affect Behavioural Intention to Adopt DFS, in contrast to the predicted theorized hypothesis (path coefficient = 0.127, t = 1.421, ns).

Facilitating Conditions (path coefficient = 0.138, t = 1.527, ns) was found not to have a significant relationship with Behavioural Intention to Adopt DFS. Contrary to expectations, this predictor showed no significance and absolute zero values were observed within its bootstrapping confidence intervals. Perceived Value had a significant and positive relationship with Behavioural Intention to Adopt DFS (path coefficient = 0.279, t = 2.880, p < 0.004). There was also no absolute zero value, as indicated by the bootstrapping confidence interval. Price Benefit had a significant and positive relationship with Behavioural Intention to Adopt DFS (path coefficient = 0.217, t = 2.755, p < 0.01). There was also no absolute zero value as shown by the bootstrapping confidence interval. Trust had a significant and

positive relationship with Behavioural Intention to Adopt DFS (path coefficient = 0.189, t = 2.055, p < 0.01). As indicated by the bootstrapping confidence interval, there was also no absolute zero value.

Similarly, the predictors Perceived Risk (path coefficient = -0.086, t = 1.086, ns), Unavailability of Facilitating Conditions (path coefficient = 0.011, t = 0.159, ns), and Perceived Cost (path coefficient = 0.027, t = 0.424, ns) were not found to have significant relationships with Behavioural Intention to Adopt DFS. Contrary to expectations, these predictors showed no significance and absolute zero values were observed within their bootstrapping confidence intervals.

4.4.4 *Test for Confounding Effects*

The demographic variables age, gender, education, and income were included and tested as controls in the estimated structural path model. These controls were tested for their potential confounding effects on the study's dependent variable behavioural intention to adopt DFS.

Age (path coefficient = 0.078, t = 1.331, p < 0.10), gender (path coefficient = -0.033, t = 0.684, p < 0.10), education (path coefficient = -0.079, t = 1.589, p < 0.10), and income (path coefficient = 0.004, t = 0.066, p < 0.10), were not found to have significant relationships with behavioural intention to adopt DFS. These demographic controls had no observed confounding effects when estimating the structural path model. Therefore, there was no observable interference on relevant research hypotheses of the present study.

4.4.5 *Summary of hypothesis*

Table 35 displays the summary of the hypothesis test results.

Summary of Results of Hypothesis Testing		
Hypothesis		**Results**
H1	Performance Expectancy will positively influence the behavioural intention to adopt DFS.	Supported
H2	Effort Expectancy will positively influence the behavioural intention to adopt DFS.	Not Supported
H3	Network Externalities will positively influence the behavioural intention to adopt DFS.	Not Supported
H4	Facilitating Conditions will positively influence the behavioural intention to adopt DFS.	Not Supported
H5	Perceived Value will positively influence the behavioural intention to adopt DFS.	Supported
H6	Price Benefit will positively influence the behavioural intention to adopt DFS.	Supported
H7	Trust will positively influence the behavioural intention to adopt DFS.	Supported
H8	Unavailability of Facilitating Conditions will negatively influence behavioural intention to adopt DFS.	Not Supported
H9	Perceived Risk will negatively influence behavioural intention to adopt DFS.	Not Supported
H10	Perceived Cost will negatively influence behavioural intention to adopt DFS.	Not Supported

Table 35: Summary of Results of Hypothesis Testing

4.5 Coefficients of Determination (R^2 Value)

The coefficient of determination (R^2 value) is the squared correlation between a certain criterion (dependent) variable's anticipated and actual value. This value denotes the total impact of the predictor variables on the outcome variable. Larger values of R^2 indicate higher prediction accuracy (Hair Jr et al., 2014).

According to Chin (1998), the R^2 value thresholds for dependent variables are substantial = 0.670, moderate = 0.333, and weaker = 0.190, respectively. Hair et al. (2014) found that these R^2 thresholds are open to interpretation and may not be conclusive, particularly in the Social Sciences and associated research. For instance, an R^2 value of 0.200 can be considered significant for Consumer Studies.

***R^2* Value of Dependent (Criteria) Variable**	
Dependent (Criterion) Variable	***R^2* Value**
Behavioural Intention to Adopt DFS	0.575

Table 36: R^2 Value of Dependent (Criteria) Variable

As shown in Table 36, the value obtained (R^2 = 0.575) indicates that the structural path model has significant predictive accuracy for the dependent (criterion) variable Behavioural Intention to adopt DFS.

4.5.1 *Effect Size (f^2)*

Calculating an f^2 effect size was conducted in addition to evaluating the overall R^2 value in the present study. When a predictor (independent) variable is excluded from the structural path model, the R^2 value of the dependent (criterion) variable changes. This change is measured by the f^2 effect. The following formula was used to determine the respective f^2 effect sizes:

$$f^2 = \frac{R^2_{\text{included}} - R^2_{\text{excluded}}}{}$$

$$1 - R^2_{\text{included}}$$

Equation 1: f^2 Effect Size

The R^2 value of the dependent variable, which includes a specific predictor variable from the path model, is referred to as R^2 included. When a specific predictor variable is excluded, the R^2 is referred to as R^2 excluded (Hair Jr et al., 2017). The study estimated the path model twice to produce the f^2 effect by estimating the changes in the R^2 values.

The independent (predictor) variables were incorporated into the path model estimation generating R^2 included values. Next, an independent variable was excluded from the path model estimation generating an R^2 excluded value. Cohen value thresholds were then applied to interpret the f^2 effect per the above formula (Cohen, 1988).

An independent variable is said to have a small effect (f^2 value between 0.020 to 0.150), medium effect (f^2 value between 0.150 to 0.350), or large effect (f^2 value greater than 0.350), on the dependent variable. Table 37 illustrates the estimated structural path model's f^2 effect sizes.

Results of f^2 Effect Sizes for Dependent (Criteria) Variable					
Independent Variable	**Dependent Variable**	**R^2 included**	**R^2 excluded**	**f^2 effect size**	**Interpretation**
Performance Expectancy	Behavioural Intention to Adopt DFS	0.575	0.558	0.04	Small Effect
Effort Expectancy		0.575	0.535	0.09	Small Effect
Network Externalities		0.575	0.569	0.01	No Effect
Facilitating Conditions		0.575	0.564	0.03	Small Effect

Perceived Value		0.575	0.546	0.07	Small Effect
Price Benefit		0.575	0.557	0.04	Small Effect
Trust		0.575	0.561	0.03	Small Effect
Unavailability of Facilitating Conditions		0.575	0.575	0.00	No Effect
Perceived Risk		0.575	0.573	0.00	No Effect
Perceived Cost		0.575	0.575	0.00	No Effect

Table 37: Results of f^2 Effect Sizes for Dependent Variables

The predictors Performance Expectancy (0.04), Effort Expectancy (0.09), Facilitating Conditions (0.03), Perceived Value (0.07), Price Benefit (0.04), and Trust (0.03) had small effects on Behavioural Intention to Adopt DFS. Additionally, the predictors Network Externalities (0.01), Unavailability of Facilitating Conditions (0.00), Perceived Risk (0.00), and Perceived Cost (0.00) had negligible effects on Behavioural Intention to Adopt DFS, each with an f^2 value of less than 0.02.

4.6 Predictive Relevance (Q^2 Value)

The Stone-Geisser's Q^2 value (Geisser, 1974; Stone, 1974) was evaluated in addition to predictive accuracy (R^2) to determine the predictive relevance of the structural path model (Hair Jr et al., 2017). Blindfolding techniques and predetermined omissions were used to determine the Q^2 value of the path model. Blindfolding is applied to the dependent variable that makes up a reflective specification of the measurement model (Hair Jr et al., 2017). The structural path model's significant predictive relevance for a particular dependent variable is indicated by Q^2 values above 0.000. However, Q^2 values below 0.000 indicate a lack of structural path model predictive relevance (Hair Jr et al., 2017).

Results of Q^2 Value of Dependent (Criteria) Variable	
Dependent Variable	***Q^2* Value**
Behavioural Intention to adopt DFS	0.295

Table 38: Results of Q2 Value of Dependent Variable

The result in Table 38 shows that the Q^2 value had significant predictive relevance for the dependent (criterion) variable Behavioural Intention to Adopt DFS (0.295). Thus, together, the latent variables (predictors) contribute to the structural path model's predictive relevance.

4.6.1 *Effect Size (q^2)*

In addition to testing the Q^2 value of the study's structural path model, the individual q^2 effect sizes of its latent (predictor) variables was evaluated. The q^2 effect size provides additional data on the relative contribution of the independent (predictor) variables on the estimated structural path model's predictive relevance Q^2.

Predictive relevance values are interpreted as minor (0.02), medium (0.15), and large (0.35), respectively. The following formula was used to calculate the respective q^2 effect sizes:

$$q^2 = \frac{Q^2_{included} - Q^2_{excluded}}{1 - Q^2_{included}}$$

Equation 2: q^2 Effect Size

Values for Q^2 included and Q^2 excluded were derived using the PLS-SEM findings. Q^2 included was determined from the previous estimation performed while blindfolded to establish a predictive relevance (Q^2) score. The value for Q^2 excluded was derived from a structural path model re-estimation after removing

the predictor variable (Hair Jr et al., 2017). Table 39 below displays the q^2 effect size of the calculated structural path model.

Results of q^2 Effect Sizes for Dependent (Criteria) Variables					
Independent Variable	**Dependent Variable**	**Q^2 included**	**Q^2 excluded**	**q^2 effect size**	**Interpretation**
Performance Expectancy	Behavioural Intention to adopt DFS	0.295	0.286	0.01	No Effect
Effort Expectancy		0.295	0.283	0.02	Small Effect
Network Externalities		0.295	0.300	-0.01	No Effect
Facilitating Conditions		0.295	0.286	0.01	No Effect
Perceived Value		0.295	0.287	0.01	No Effect
Price Benefit		0.295	0.287	0.01	No Effect
Trust		0.295	0.285	0.01	No Effect
Unavailability of Facilitating Conditions		0.295	0.296	0.00	No Effect
Perceived Risk		0.295	0.293	0.00	No Effect
Perceived Cost		0.295	0.296	0.00	No Effect

Table 39: Results of q^2 Effect Sizes for Dependent Variables

Among the hypothesised determinants, only Effort Expectancy (0.02), had a significant predictive relevance for the target variable Behavioural Intention to

Adopt DFS. The researcher however noted that whereas as a collective, the latent variables contribute to the significant predictive relevance ($Q^2 > 0$) of the study's structural path model ($Q^2 = 0.295$), the predictors Performance Expectancy (0.01), Network Externalities (-0.01), Facilitating Conditions (0.01), Perceived Value (0.01), Price Benefit (0.01), Trust (0.01), Unavailability of Facilitating Conditions (0.00), Perceived Risk (0.00), and Perceived Cost (0.00), were observed to have minor or negligible individual q^2 effect sizes.

4.7 Post-Hoc Analysis

4.7.1 *Importance-Performance Map Analysis (IPMA) Test*

Following structural path model tests, a post-hoc test (one exceeding the scope of relationships hypothesised and empirically examined in the study) was conducted. While not theorised a priori, an Importance-Performance Map Analysis (IPMA) was applied to enrich PLS-SEM testing by considering the individual performance of each latent variable in the analysis (Hair et al., 2018).

In the study, four-steps were followed to conduct an IPMA test for the target construct behavioural intention to adopt DFS.

First, indicator data for the study were confirmed to have been measured using an equidistant (5-point Likert) scale i.e. one that has two balanced negative and positive anchors, and a neutral option. Further, all indicators were confirmed to have the same scale direction i.e. positive. A PLS-SEM algorithm was then run to examine all indicator weights to ensure only positive values. Second and third, the IPMA test was run via PLS-SEM to compute importance and performance scores. Fourth, these scores were used to output an importance-performance map, with an x-axis representing total effects (importance), and y-axis for rescaled latent variable scores (performance).

To interpret this mapping, focus is placed on the predecessor (predictor) constructs in the lower-right quadrant of the importance-performance map. This region is concerned with those constructs that show a high importance, yet low

performance, for the target construct which are then identified as areas of improvement for managerial or policy action (Hair et al., 2018).

IPMA values for behavioural intention as the target construct, are summarized in Table 40.

Target: Behavioural Intention to Adopt Digital Financial Services (DFS)		
Predecessor	**Importance (Total Effects)**	**Performance (Index Values)**
Performance Expectancy	0.209	59.713
Effort Expectancy	-0.306	55.462
Facilitating Conditions	0.146	65.502
Network Externalities	0.121	44.736
Price Benefit	0.221	46.890
Perceived Value	0.263	54.828
Trust	0.185	54.819
Unavailability of Facilitating Conditions	0.007	49.948
Perceived Risk	-0.090	56.523
Perceived Cost	0.040	47.976
Mean Value	**0.080**	**53.640**

Table 40: Summary of the Importance-Performance Map Analysis (IPMA) for Behavioural Intention to Adopt DFS

Table 40 shows that performance expectancy had the highest performance for predicting behavioural intention to adopt DFS, with an importance score well

above average. Perceived value had the highest importance value (well above average) whilst showing a slightly above average performance.

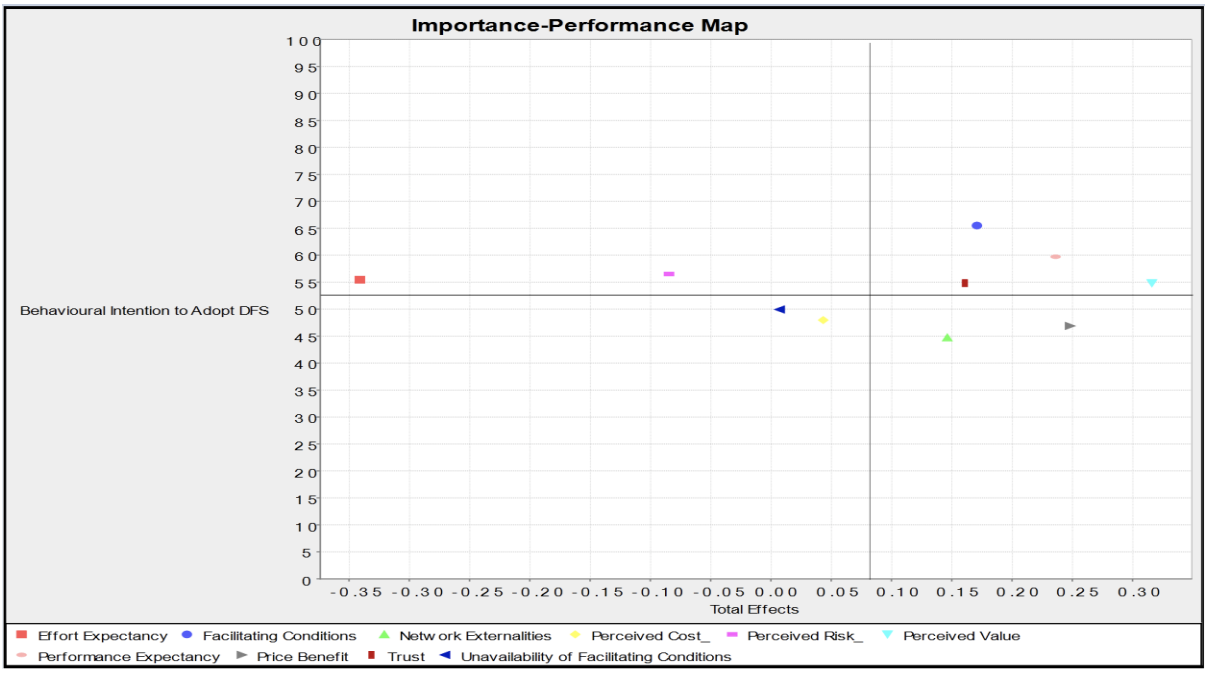

Figure 8: Importance-Performance Map for the Behavioural Intention to Adopt DFS Construct

More importantly, as mapped in Figure 8, managerial or policy activities to enhance adoption intention behaviour should be concentrated on the network externalities and price benefits constructs.

Among the predecessor constructs, price benefits (total effect = 0.221, index value = 46.890) and network externalities (total effect = 0.121, index value = 44.736) had the greatest importance with correspondingly below average relative performance scores, respectively. Thus, findings indicated a relatively high potential for improving the performance of price benefits and network externalities, to enhance behavioural intention to adopt DFS.

Notably, as one of only two predecessors that fall in the lower-right quadrant of the importance-performance map (Figure 8), price benefits is the most important predecessor with the lowest performance, thereby signifying the greatest opportunity for improvement.

All things being equal, an increase in the performance of price benefits by one unit (from 46.9 to 47.9) would result in an increase in the performance of behavioural intention to adopt DFS by the size of this predecessor's total effect (0.221), on the levels of behavioural intention to adopt DFS. Similarly, an increase in the performance of network externalities by one unit (from 44.7 to 45.7) would result in an increase in the performance of behavioural intention to adopt DFS by the size of this predecessor's total effect (0.121), on the levels of behavioural intention to adopt DFS.

These findings show that price benefits and network externalities can likely and increasingly play a key role in influencing behavioural intention to adopt DFS despite their low performance, thus warranting managerial or policy-focused intervention.

4.8 Conclusion

This chapter detailed results of analysis using research methods employed for the study as described in Chapter 3. The study's findings are discussed in detail in the following chapter. The conclusions of this chapter will be reflected upon on the basis of the study's theoretical underpinnings in relation to the review of existing literature conducted in Chapter 2.

CHAPTER 5. DISCUSSION OF THE RESULTS OR FINDINGS

5.1 Introduction

This chapter reflects on the study's hypotheses as well as the influences of several identified independent factors on the dependent variable Behavioural Intention to Adopt DFS. These factors were hypothesized to influence DFS adoption behaviour at the individual-level, drawing on prior research on adoption models and DFS technology. Empirical findings from the preceding chapter are discussed with explanations of observed outcomes based on theoretical foundations of the study's conceptual model and context of the current investigation.

5.2 The Relationship between Performance Expectancy and Behavioural Intention to adopt DFS

Hypothesis 1 (H1) was supported. It was found that performance expectancy was identified as a significant factor in determining behavioural intention to adopt DFS as per the reviewed literature (Madan & Yadav, 2016; Rahi et al., 2019; V. Venkatesh et al., 2012). The literature reviewed aligns with the finding of this study indicating that South African users are more likely to adopt DFS or "Fintech" if these technologies make their lives simpler and services more accessible (Slazus & Bick, 2022). Moreover, given that SASSA grant holders generally do not use technology and prefer cash (Financial Sector Conduct Authority & Genesis Analytics, 2022), it is reasonable that the easier it is to use the technology, the more likely this group of users will adopt it.

5.3 The Relationship between Effort Expectancy and Behavioural Intention to adopt DFS

Hypothesis 2 (H2) was not supported. Effort Expectancy is found in the existing literature to have an insignificant effect on the behavioural intention to adopt DFS

(Hassan et al., 2022; Madan & Yadav, 2016; Qasim & Abu-Shanab, 2016; Shaw & Sergueeva, 2019; Urus et al., 2022; Wei et al., 2021). Some studies have also evidenced a positive relationship with behavioural intention to adopt DFS (Rahi et al., 2019; Singh & Travica, 2018; Slazus & Bick, 2022). The present study found that Effort Expectancy had a significant negative relationship with behavioural intention to adopt DFS. A negative relationship between Effort Expectancy and behavioural adoption intention was found by Zuiderwijk et al (2015), who conducted a similar study on open data technologies. Their study observed that although some participants found it easy to use open data technologies, this did not indicate that the respondents would use them. This negative relationship was attributed to the different barriers which existed for the participants, which increased their effort expectancy for open data usage and acceptance (Zuiderwijk et al., 2015). These barriers were identified as the difficulty of obtaining open datasets that one is looking for, certain data sets not being accessible by participants, differing skills in Internet usage, and participants having different capacities to access and use open data (Zuiderwijk et al., 2015). SASSA grant holders, like open data technology users, have different barriers which impact their ease of use. These barriers include digital illiteracy, limited access to technology, lack of Internet connectivity, language barriers, and transaction fees (Mozilla Foundation, 2017; Venter et al., 2019). These barriers could possibly have resulted in a negative relationship for Effort Expectancy in the present study.

5.4 The Relationship between Network Externalities and Behavioural Intention to adopt DFS

Hypothesis 3 (H3) was not supported. Network Externalities is closely related to Social Influence (Pal et al., 2020). Social Influence as a factor has been studied extensively, as there is existing literature which evidences that Social Influence has an insignificant effect on behavioural adoption intention (Alhajjaj & Ahmad, 2022; Mazambani & Mutambara, 2020; Shaw & Sergueeva, 2019; Singh et al., 2020; Urus et al., 2022). In the present study, Network Externalities could be insignificant due to participants treating financial matters with secrecy and privacy

and thus having no reliance on others to influence their adoption behaviours (Mazambani & Mutambara, 2020). Mazambani & Mutambara (2020) also noted that South Africa's financial market being hit by numerous Internet-based financial scams may dissuade participants from succumbing to social pressure and thus could reinforce why the present study evidenced an insignificant effect between Network Externalities and Behavioural intention to adopt DFS. This observation in South Africa, is no different from observations from prior research conducted in the context of developing nations such as India, Malaysia, and Jordan, where an insignificant effect was found between Social Influence and adoption intention behaviours (Alhajjaj & Ahmad, 2022; Singh et al., 2020; Urus et al., 2022).

5.5 The Relationship between Facilitating Conditions and Behavioural Intention to adopt DFS

Hypothesis 4 (H4) was not supported. In the existing literature, some studies found Facilitating Conditions to have a significant positive relationship with behavioural intention (Hassan et al., 2022; Madan & Yadav, 2016; Rahi et al., 2019). Other studies found in accordance with this study that Facilitating Conditions has an insignificant relationship with behavioural intention (Shaw & Sergueeva, 2019; Wei et al., 2021; Xie et al., 2021). According to Venkatesh et al (2003), the relationship between facilitating conditions and behavioural intention would disappear when including effort expectancy in the model (Urus et al., 2022; V. H. Venkatesh et al., 2003). Therefore, the results of this study align with Venkatesh et al (2003)'s findings, as the inclusion and significance of Effort Expectancy may have resulted in insignificant results for Facilitating Conditions. This disappearing effect could result from participants confusing ease of use with facilitating conditions (Shaw & Sergueeva, 2019; V. H. Venkatesh et al., 2003). This is plausible for the present study due to the significant negative effect of Effort Expectancy coupled with the user perception among SASSA grant holders that the DFS tool is easy to use.

5.6 The Relationship between Perceived Value and Behavioural Intention to adopt DFS.

Hypothesis 5 (H5) was supported. It was found that Perceived Value was a very significant factor in keeping with the literature (Madan & Yadav, 2016; Shaw & Sergueeva, 2019; Xie et al., 2021). According to Xie et al (2021), this conclusion is aligned with the behavioural decision theory, based on the premise that a consumer's decision behaviour depends on recognising trade-offs between the quality of the decision and effort expended to make that decision. Some studies also evidence a relationship between Perceived Value and Performance Expectancy or Effort Expectancy (Shaw & Sergueeva, 2019; Xie et al., 2021). Although these relationships were not investigated in this study, it is observed that both PE and EE have significant relationships with adoption intention behaviours. This is similar to the finding observed for Perceived Value in the present study. This finding means that if a SASSA grant holder compares the trade-offs and the ease of using a DFS tool to using cash and sees value, then they would use the former. As such, a positive reaction among users towards the adoption of a DFS tool was observed in the present study.

5.7 The Relationship between Price Benefit and Behavioural Intention to adopt DFS

Hypothesis 6 (H6) was supported. In a study in India on Mobile Wallet adoption, it was determined that incentives provided by service providers to drive adoption had a positive significant relationship with adoption intention behaviour (Madan & Yadav, 2016). In a study where the continued use of mobile payment services in India evidenced that incentives have an insignificant relationship with behavioural intention, Pal et al (2020) acknowledged that these benefits drive initial adoption but are insignificant for continued use. The present study evidenced that incentives (Price Benefits) was supported, and this could be the result of the targeted population and their circumstances. In South Africa, SASSA grants holders are a population group known to be part of low-income households. Thus, the cost of using DFS is important to them. As such, any

incentive will more than likely sway participants to be able to adopt DFS, therefore reinforcing the positive relationship observed in the present study.

5.8 The Relationship between Trust and Behavioural Intention to adopt DFS

Hypothesis 7 (H7) was supported. It was found that Trust was a very significant factor consistent with the existing literature (Hassan et al., 2022; Kurniasari et al., 2022; Madan & Yadav, 2016; Pal et al., 2020; Qasim & Abu-Shanab, 2016; Slazus & Bick, 2022). The literature further highlights the importance of trust when it comes to monetary transactions (Hassan et al., 2022; Pal et al., 2020; Qasim & Abu-Shanab, 2016). Therein a distinction is made between trust in the DFS technology tool itself and the service provider, whereby both are required (Qasim & Abu-Shanab, 2016). This study focused on service providers as the technology investigated in the present study is an existing tool currently being used in South Africa (bank cards). In South Africa, due to the various corruption charges preferred against the government, South Africans do not trust their governance institutions (Moosa & Hofmeyr, 2021). This lack of trust is demonstrated by a lack of DFS adoption among SASSA grant users. Further, this is attributed to SASSA being an entity of the South African government through the Department of Social Development (Department of Social Development, 2022). According to Pal et al (2020), “low-income communities have high financial sensitivity”. This sensitivity is what makes trust an important factor. Hence, a significant positive relationship was observed in the present study.

5.9 The Relationship between Unavailability of Facilitating Conditions and Behavioural Intention to adopt DFS

Hypothesis 8 (H8) was not supported. This finding is in line with the existing literature (e.g. Pal et al., 2020). In some prior studies highlighted from the existing literature, findings following empirical tests conducted evidenced a significant relationship between ‘facilitating conditions’ and DFS tools such as mobile wallets and “Fintech” services (Hassan et al., 2022; Madan & Yadav, 2016; Rahi et al.,

2019). In other works, significant effects were not found (Shaw & Sergueeva, 2019; Wei et al., 2021; Xie et al., 2021). In an empirical study conducted to investigate the Unavailability of Facilitating Conditions as a construct of adoption in India, an insignificant effect was observed (Pal et al., 2020). The present study was an investigation in South Africa on the DFS tool available to SASSA grant holders called a SASSA card. This tool works as per a normal bank account card and thus, its underlying infrastructure has been available since the 1980s (Haridass, 2020).

5.10 The Relationship between Perceived Risk and Behavioural Intention to adopt DFS

Hypothesis 9 (H9) was not supported. Of note, perceived risk was not found to have a significant effect on adoption intention behaviour. This finding aligns with other research conducted in emerging nations including South Africa (Hassan et al., 2022; Hu et al., 2019; Jenkins & Ophoff, 2016). In their work, Hassan et al (2022) observed that insufficient understanding of risk could be what results in the insignificant effects they observed. Various studies highlighted in the existing literature evidenced a significant positive relationship between Trust and Perceived Risk (Hassan et al., 2022). A significant negative relationship between Trust and Perceived Risk was also observed (Jenkins & Ophoff, 2016). The present study was not focused on examining this relationship. However, a perceived lack of trust among participants can explain why this factor was not found to have a significant effect. As previously discussed, the participants do not trust the government, and thus, the social grant recipients do not believe or consume any communicated information to them. If this distrust is significant, the result could be recipients disinterested in technology adoption such that any risks identified are of no concern. This phenomenon can be deduced from the relationship between Trust and Perceived Risk identified by Jenkins and Ophoff (2016).

5.11 The Relationship between Perceived Cost and Behavioural Intention to adopt DFS

Hypothesis 10 (H10) was not supported. Notably, this study evidenced that Perceived Cost does not have a significant effect on behavioural intention. There are a number of reasons that perceived cost could be statistically significant. Firstly, although cost is an important factor for social grant recipients as money is limited and they fall within the lower Living Standards Measure (LSM), this group is not known to use digital technology. Therefore, this could result in this factor not being an effective determinant of adoption behaviour. Secondly, there may be other factors like Trust, Performance Expectancy, Effort Expectancy, Perceived Value, and Price Benefit, which are more important determinants among the participants for their behavioural intention to adopt DFS. Lastly, the cost of using a SASSA card differs from the perceived cost, as evidenced in the existing literature. Hence, a discrepancy, although not unusual, between the empirical results of the present study and findings from the existing literature was observed.

5.12 Conclusion

Considering the research questions from Chapter 1 and the stated hypothesis from Chapter 2, this chapter reviewed the research findings in conjunction with those from the existing literature on DFS and technology adoption intention behaviour. Findings following empirical tests of the study's proposed hypotheses and variations in results across contexts were also discussed. While some of the findings were consistent with the literature, new viewpoints also arose in the explanations pertaining to findings of the study. The key research findings are summarized in Chapter 6, with reflections on the implications of the findings for future research and management practice, will be discussed. Furthermore, in concluding the report, the present study's limitations, will be discussed.

CHAPTER 6. CONCLUSIONS & RECOMMENDATIONS

6.1 Introduction

In the preceding chapters, South Africa's financial sector and social grant recipients were discussed in relation to the adoption of DFS. As per the existing DFS literature, the adoption of technology by individuals was discussed. A research model was created, with the underpinning theoretical frameworks outlined in Chapter 2. The research methodology used in the present study and methods implemented to collect data, were presented in Chapter 3. Empirical data were analysed in Chapter 4, and the results of hypotheses testing were discussed in Chapter 5. The study is summarised in this chapter, and the implications of its findings for stakeholders are described. The study is then concluded once limitations and opportunities for future research are identified.

6.2 Summary of the Study

The review of existing literature on DFS adoption revealed the need to measure individual user adoption in South Africa because users directly interact with DFS tools. It was further discovered that UTUAT is the most widely used model focusing on adoption and thus expanding the model with additional theoretical literature to identify all factors impacting adoption. The present study was informed by a lack of adoption of DFS in South Africa, with the country being a cash-based economy despite significant penetration of mobile devices.

The present study identified a set of adoption factors that can have an impact on individual adoption and usage of DFS technology. A review of the literature on DFS and technology adoption, as well as barriers to adoption and technology readiness, resulted in the identification of ten (10) independent variables underpinned by selected theories. These variables were then hypothesised as being positively or negatively related to behavioural intention to adopt DFS.

Tests for validity and reliability were conducted after data elicited for the present study were screened. Descriptive statistics were used to answer the study's research questions. Regression using PLS modelling were used to test the hypotheses via predictive path analysis. Five factors were observed to have a significant influence on Behavioural Intention to adopt DFS in South Africa. These were Performance Expectancy, Effort Expectancy, Perceived Value, Price Benefit, and Trust. Further, following post-hoc analysis (IPMA), it was found that that Network Externalities and Price Benefits are the constructs with high importance and relatively low performance, and identified as key potential areas for managerial or policy-related intervention that could enhance behavioural intention to adopt DFS among SASSA grant holders per the study's empirical context.

6.3 Implications for Stakeholders

This study's implications for research (academia) and practice are discussed in this section.

6.3.1 *Academic Contribution*

There has been a significant study in technology adoption and the use of the UTAUT and UTAUT 2 model. This study provided an academic contribution by expanding the UTAUT model through the inclusion of elements from the TRI and Resistance of New Innovation. The expanded model revealed that Effort Expectancy is an inhibitor to adoption, and Perceived Value and Trust are key considerations to include in the UTAUT model in the South African context when investigating social grant recipient adoption.

The study also provides a view on technology adoption in South Africa for a population which uses cash and is not part of the existing financial sector. This context and view provide a first step towards understanding why this population is not adopting DFS technology and what factors can affect adoption. Academia can use the extended model to understand the impact of these factors on users

of cash, not on social grants in South Africa, to fully understand the phenomenon of a cash-based society with high technology penetration.

Post-hoc analysis conducted provides a view of which constructs requires subsequent improvement from a managerial or policy-related perspective. The study determined Network Externalities and Price Benefit as high potential areas for improvement. These findings allow for academics to determine what the impacts of addressing these constructs would be for behavioural intention to adopt DFS.

6.3.2 *Practical Contribution*

The study highlighted key aspects of DFS tool usage behaviour of social grant holders in South Africa.

Financial Institutions and other service providers, like Banks and “fintechs”, are introducing digital payments in South Africa to capture customers currently not using digital payments. These financial institutions can use the factors observed to have significant effects evidenced in the present study to determine strategies that will assist them in embedding their products and ensuring adoption. The strategies should also be implemented when designing the DFS tool, as Performance Expectancy and Effort Expectancy are factors that were determined to affect adoption significantly. Financial Institutions should consider prioritising Network Externalities and Price Benefits when implementing solutions to address DFS adoption, as these two indicators are low performing factors, although of high importance.

Government can use this study and the practical implications that the factors’ effects indicate when documenting policies to drive financial inclusion and provide oversight to financial institutions. Governments can also prioritise the various indicators by using the evidence-based (data-driven) Importance-Performance Map approach to empirical analysis as demonstrated in the study. Further, Government should prioritise policies that focus on improving the performance of Network Externalities, by driving social awareness and driving digital inclusion.

SASSA, as an organisation, should focus on strategies to improve the trust relationship that exists between themselves and consumers of their DFS tool. SASSA should work with Fast-Moving Consumer Goods (FMCG) and other financial institutions to provide additional benefits for using their DFS tool to drive adoption and usage of the card. SASSA should also prioritise improving the performance of Price Benefits due to its low performance index despite its high potential influence. Campaigns highlighting the digital tool's benefits and how to use it, and where social grant recipients are involved, can be conducted. To assist the digitally illiterate, SASSA can assist recipients using their indigenous languages. The above addresses the factors which are determined to affect DFS adoption.

6.3.3 *Global Contributions*

The use of cash is not just a South African problem. As mentioned in Chapter 2, the study can be used to determine whether similar behaviour by social grant recipients in other emerging countries is similar. Academics are able to use the social grant recipient's behaviour in South Africa to understand how this group populates in other emerging countries where DFS adoption is low, and it is a cash-based economy. Governments in emerging countries that administer social grants can use this study and findings to drive the adoption of their DFS tools for the non-banked consumer segment in their countries.

6.4 Suggestions for further research

The present study provides new directions for future studies on the individual adoption of DFS in the South African context.

First, the population group identified to conduct the study is social grant holders in identified municipalities within South Africa. The use of this population group limits the study and allows for further research on expanding the population by targeting social recipients from other South African municipalities or provinces. Expanding this scope will allow for a broader South Africa view of DFS adoption.

Second, the present study focused on social grant recipients to inform the empirical testing of DFS adoption behaviours. Future research should include South Africans who are not social grant holders but also use cash and not DFS tools when conducting their payments. The sample pooled for the present study allowed the researcher to generalise the study's findings to the South African population.

Third, DFS consists of various tools like digital remittance and digital lending. This study focused on digital payments using DFS tools. Future researchers should conduct research investigating different DFS capabilities for application in settings such as lending, remittances, or savings. This kind of research would provide an overall view of DFS holistically in South Africa.

Fourth, Price Benefit and Network Externalities, which were determined to have low performance while high importance can be further investigated. Further research should concern the ways in which Price Benefits and Network Externalities can be enhanced to more strongly influence behavioural intention to adopt DFS. Additional research can also investigate why these two indicators are underperforming, and how this trend can be reversed to further enable behavioural intention to adopt DFS.

Lastly, the reviewed existing literature evidenced that some of the independent variables e.g. Trust and Perceived Risk, are interrelated. The scope of the present study does not, however, constitute an investigation of these relationships in relation to adoption behaviour. Future research should examine the effect of the interrelations between independent variables and their impact on individual adoption.

6.5 Chapter Conclusion

There is significant research on DFS adoption at the individual user level across many emerging countries in Africa and worldwide. However, there has been little attention afforded to the South African context and social grant holders in particular. It is important that all South Africans are further introduced to DFS to ensure that the benefits received from technology adoption are widespread,

especially among marginalised communities. The present study drew on the existing literature on DFS and technology adoption, barriers to adoption, and technology readiness. Furthermore, the findings of the study have improved our understanding of how behavioural intention to adopt DFS is primarily influenced by Performance Expectancy, Price Benefit, Perceived Value, and Trust factors. The study also enhanced our understanding of how Effort Expectancy can have a negative influence where different extensive barriers may exist for a given population of potential users. These findings are important for the investigation and implementation of DFS in South Africa in a concerted effort to address the existing gap of social grant recipients who have been excluded from the financial economy.

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APPENDIX A: Digital Financial Services (DFS) and Fintech Literature Reviewed

Study Title	Study	Aim of Study	Research Type
Factors that influence Fintech Adoption in South Africa: A Study of Consumer Behaviour towards Branchless Mobile Banking	(Slazus & Bick, 2022)	Determine enabling and inhibiting factors that influence the adoption of Fintech and mobile banking services in the South African market.	Mixed Methods Research
Adoption Factors of Fintech: Evidence from an Emerging Economy Country-Wide Representative Sample	(Mahmud et al., 2022)	Investigate Fintech adoption, usage, readiness, and impact on sustainable economic development in Bangladesh.	Quantitative Research
COVID-19's Impact on Fintech Adoption: Behavioral Intention to Use the Financial Portal	(Shahzad et al., 2022)	Determine the factors influencing the consumers' attitude towards the adoption of Fintech services (loan aggregator portal: MyAzZahra).	Quantitative Research
Drivers of the Consumer's Adoption of Fintech services	(Alhajjaj & Ahmad, 2022)	Investigate the impact of environmental factors and trust on the consumer's	Quantitative Research

		behavioural intention to adopt Fintech services in Jordan.	
A comparative study of Fintech payment services adoption among Malaysian and Indonesian fresh graduates: Through the lens of UTUAT theory	(Urus et al., 2022)	A comparative study to analyse the adoption of Fintech payment services by recent graduates in Malaysia and Indonesia using the UTAUT model.	Quantitative Research
Drivers Influencing the Adoption Intention towards Mobile Fintech Services: A Study on the Emerging Bangladesh Market	(Hassan et al., 2022)	Identify the factors that impact the adoption intention of consumers to embrace mobile fintech services. Moreover, enhance the use of mobile fintech services in an emerging market.	Cross-sectional and Quantitative Research
Determinant Factors of Adoption of Fintech Payment Services in Indonesia using the UTAUT Approach	(Kurniasari et al., 2022)	Analyse the adoption of Fintech payment services in Indonesia using the UTAUT theory approach.	Quantitative Research

Understanding Fintech Platform Adoption: Impacts of Perceived Value and Perceived Risk	(Xie et al., 2021)	Investigate the factors that affect individuals' acceptance of Fintech services (internet wealth platforms)	Quantitative Research
Contextual facilitators and barriers influencing the continued use of mobile payment services in a developing country: insights from adopters in India	(Pal et al., 2020)	Investigate what the contextual facilitators and barriers that drive mobile payment usage.	Quantitative
What drives Fintech adoption? A multi-method evaluation using an adapted technology acceptance model	(Singh et al., 2020)	Develop a framework to examine Fintech adoption and use from the technology acceptance perspective by adding sub-constructs of the technology acceptance model (TAM), unified theory of acceptance and use of technology (UTAUT)	Quantitative Research
Predicting Fintech innovation adoption in South Africa: the case of cryptocurrency	(Mazambani & Mutambara, 2020)	Apply the theory of planned behaviour (TPB) to predict behavioural intention to adopt cryptocurrency.	Cross-sectional and Quantitative Research

SMEs' Intention towards Use and Adoption of Digital Financial Services	(Khan & Siddiqui, 2019)	Analyse the SMEs owner's and managers' intentions to use and adopt digital financial services.	Quantitative Research
Predicting the attitude towards electronic banking continued usage intentions among rural banking customers in South Africa.	(Nkoyi et al., 2019)	Investigate attitude formation towards e-banking continued usage intention among rural banking customers.	Quantitative Research
The Influence of Perceived Risk and Trust in the Adoption of Fintech Services in Indonesia	(Meyliana et al., 2019)	Investigate the adoption of Fintech services in terms of risk and trust.	Quantitative Research
Behavioural intention to adopt mobile wallet: a developing country perspective	(Madan & Yadav, 2016)	Investigate and understand the factors that affect a consumer's adoption of mobile wallet in India	Quantitative Research
An empirical investigation of mobile data service continuance: Incorporating the theory of planned	(Kim, 2010)	Investigate a user's continuous behaviour towards mobile data service based on expectation and behaviour	Quantitative Research

behaviour into the expectation-confirmation model			

APPENDIX B: Participant Information Sheet

Cover Letter (Participant Information Sheet)

Dear Sir/Madam,

My name is Olwethu Bodlani, and I am a master's student at the University of the Witwatersrand (WITS), Johannesburg.

I am conducting a study to evaluate a set of factors (predictors) that affect potential users' behavioural intention to adopt Digital Financial Systems (DFS).

This study is designed for the testing of a predictive research model of DFS adoption behaviour in the context of South Africa.

I hereby invite you to take part in this study by completing this questionnaire. There are no right or wrong answers. You have been invited to participate in this study because you use traditional cash-based systems to make payments and have been identified as a potential adopter of digital payment tools through the use of your SASSA social grant cards or mobile phones you own or have access to.

Participation in this survey is completely voluntary and involves no risk, penalty, or loss of benefits. In the event that there is a misunderstanding, the research will not invoke any payment. You have the right to withdraw from the survey at any time. You will not be required to provide your personal details or reveal your identity while answering the questionnaire.

The survey is both confidential and anonymous, and the data collected will only be used for the study and no other purpose. By filling in this questionnaire, you will be consenting to participate in the study. A summary of the survey findings will be made available upon your request.

The survey questionnaire consists of 38 statements. Please select the number that reflects the extent to which you agree or disagree with each statement. The entire questionnaire should take approximately 15 minutes to complete. Completion of this questionnaire will be taken as your consent to participate.

Should you have any queries or wish to obtain a copy of the results of the survey, please contact me on +27 72 478 8990. You can also reach me through electronic mail (e-mail) correspondence at 689588@students.wits.ac.za.

For concerns about the ethical procedures of this study, you are welcome to contact the University Human Research Ethics Committee (HREC Non-Medical) by telephone on +27 11 717 1408, or the Ethics Administrative Officer through electronic mail (e-mail) on Shaun.Schoeman@wits.ac.za

Thank you for considering your participation

Yours Sincerely,

Mr. Olwethu Bodlani

Wits Business School (WBS) Master of Management in Digital Business (MMDB) Student,

University of the Witwatersrand (WITS),

Johannesburg, South Africa (SA)

APPENDIX C: Research Instrument

SECTION A: **BIOGRAPHICAL INFORMATION**

Please indicate your response by ticking the appropriate boxes below.

1. **Age**

Below 20 years ☐ 21 - 30 years ☐ 31 - 40 years ☐

41 - 50 years ☐ 51 - 60 years ☐ 60 years and above ☐

Prefer not to say ☐

2. **Gender**

Male ☐ Female ☐ Prefer not to say ☐

3. **Marital Status**

Single/Never Married ☐ Married/Living together ☐

Divorced/Separate ☐ Widowed ☐

Prefer not to Say ☐

4. **Number of Children (Family Size)**

None ☐ 1 to 2 children ☐ 3 to 4 children ☐ 5 or more children ☐

5. **Highest Level of Education**

Primary School (Basic) ☐ High School (Matric) ☐ Diploma ☐

No Formal Education ☐ Other (Please specify) _____

6. **Annual (Yearly) Income**

Less than R 10 000	☐	R 10 000 – 30 000	☐	R 30 000 – 54 000	☐
R 54 000 and above	☐	No Income	☐	Do Not Know	☐

7. **Employment Status**

Full-Time Employee	☐	Part-Time Employee	☐	Unemployed	☐

Other (Please specify) _____

SECTION B: DIGITAL FINANCIAL SERVICES ADOPTION

1. Performance Expectancy

For each statement, please **circle** the number that best reflects the extent you agree with the following statements.		**Strongly disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly agree**
1.	I find the SASSA Card useful in my daily life.	1	2	3	4	5
2.	Using the SASSA Card increases my chances of finishing important tasks (e.g., paying for electricity and transport costs).	1	2	3	4	5
3.	Using SASSA Card helps me finish tasks like buying groceries and paying for electricity more quickly.	1	2	3	4	5
4.	Using SASSA Card increases my productivity (e.g., farming to feed my family).	1	2	3	4	5

2. Effort Expectancy

For each statement, please **circle** the number that best reflects the extent to which you agree with the following statements.		**Strongly disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly agree**
1.	Learning how to use the SASSA Card is easy for me.	1	2	3	4	5
2.	My interaction with the SASSA Card is clear and understandable.	1	2	3	4	5

3.	I find the SASSA Card easy to use.	1	2	3	4	5
4.	It is easy for me to learn how to use the SASSA Card.	1	2	3	4	5

3. Network Externalities

For each statement, please **circle** the number that best reflects the extent to which you agree with the following statements.		**Strongly disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly agree**
1.	I am swiping my SASSA Card instead of paying cash at the shops because the shops near me have swiping machines.	1	2	3	4	5
2.	I am using SASSA Card instead of other payment options because the people I buy from have card machines.	1	2	3	4	5
3.	I am using the SASSA Card instead of other payment options (e.g. cash) because my friends, family, and colleagues use it.	1	2	3	4	5

4. Facilitating Conditions

For each statement, please **circle** the number that best reflects the extent to which you agree with the following statements.		**Strongly disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly agree**
1.	I have the resources, for example, an account needed to use a SASSA Card.	1	2	3	4	5
2.	I know how to use the SASSA Card.	1	2	3	4	5
3.	The SASSA Card is compatible with other technologies (e.g., cellphones) I use.	1	2	3	4	5
4.	I can get assistance from others when I have difficulties using the SASSA Card.	1	2	3	4	5

5. Perceived Value

For each statement, please **circle** the number that best reflects the extent to which you agree with the following statements.		**Strongly disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly agree**
1.	I am getting good value using my SASSA Card for example easy and quick access to grant.	1	2	3	4	5
2.	The SASSA card provides me with additional value (e.g., ease of use in card machines).	1	2	3	4	5
3.	Compared to other payment methods (e.g. e-wallet) it is wise to choose this SASSA Card.	1	2	3	4	5

6. Trust

For each statement, please **circle** the number that best reflects the extent to which you agree with the following statements.		**Strongly disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly agree**
1.	I believe that SASSA Card service providers keep their promises and commitments of allowing me as a user to be able to use my card to buy things easily.	1	2	3	4	5
2.	I believe that SASSA Card service providers keep their customers' interests in mind.	1	2	3	4	5
3.	I believe that SASSA Card service providers are trustworthy.	1	2	3	4	5
4.	I believe that SASSA Card service providers will do everything possible to secure user transactions.	1	2	3	4	5

7. Price Benefit

For each statement, please **circle** the number that best reflects the extent to which you agree with the following statements.		**Strongly disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly agree**
1.	I am using the SASSA Card because SASSA Card provides possible discounts and cashback when I use the card.	1	2	3	4	5

2.	I am using the SASSA Card because I save money when I pay through it.	1	2	3	4	5
3.	I am using the SASSA Card tool because, at the current price, it provides good value by being the cheapest card to use.	1	2	3	4	5

8. Perceived Risk

For each statement, please **circle** the number that best reflects the extent to which you agree with the following statements.		**Strongly disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly agree**
1.	When I use the SASSA Card, I feel that I may lose money due to unforeseen mistakes.	1	2	3	4	5
2.	When I use the SASSA Card, I feel that I may not get refunds in case of transaction errors.	1	2	3	4	5
3.	When I use the SASSA Card, I feel there are chances of potential theft.	1	2	3	4	5
4.	When I use the SASSA Card, I feel that the service provider may make mistakes and process payments incorrectly.	1	2	3	4	5

9. Unavailability of Facilitating Conditions

For each statement, please **circle** the number that best reflects the extent to which you agree with the following statements.		**Strongly disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly agree**
1.	I am not able to use the SASSA Card because I do not have an active SASSA Card with me when I perform important tasks (e.g. paying for electricity and transport costs).	1	2	3	4	5
2.	I am not able to use the SASSA Card because the SASSA account cannot be linked to my bank account.	1	2	3	4	5
3.	I am not able to use the SASSA Card because I cannot operate how the card works.	1	2	3	4	5

10. Perceived Cost

For each statement, please **circle** the number that best reflects the extent to which you agree with the following statements.		**Strongly disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly agree**
1.	The fee I must pay for using the SASSA Card is too high.	1	2	3	4	5
2.	The fee I must pay for using the SASSA Card is reasonable and not too high (reversed).	1	2	3	4	5
3.	I am pleased with the fee I have to pay for using the SASSA Card (reversed).	1	2	3	4	5

11. Behavioural Intention

For each statement, please **circle** the number that best reflects the extent to which you agree with the following statements.		**Strongly disagree**	**Disagree**	**Neutral**	**Agree**	**Strongly agree**
1.	Given a chance, I intend to use the SASSA Card for payments in future.	1	2	3	4	5
2.	I will always try to use the SASSA Card in my daily transactions.	1	2	3	4	5
3.	I plan to use the SASSA Card to transact (conduct payment) frequently in the future.	1	2	3	4	5

Thank you very much for your participation

APPENDIX D: Ethics Clearance Certificate

Graduate School of Business Administration
University of the Witwatersrand, Johannesburg

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

Ethics Clearance Certificate

Ethics protocol number: WBS/DB689588/838
This certificate is only valid with a legitimate ethics protocol number and signed by the Researcher (belo

This certificate is only valid if accompanied by formal permission from the relevant stakeholder(s).

Project title	The behavioural intention to adopt digital financial services in South Africa
Investigator / Researcher	Mr Olwethu Vuyo Nkosi Bodlani
Nature of Project	MM (Digital Business)
Decision of the Committee	Approved, provided stakeholders and participants are guaranteed anonymity and confidentiality.
Issue Date of Certificate	2022-10-21
Expiry date	Date of submission of the project / research report
Chairperson	Prof Anthony Stacey ☎ +27 11 717 3587 +27 82 880 4531 anthony.stacey@wits.ac.za

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Declaration by Researcher

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

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

Signature

21 October 2022
Date: