Exploring factors influencing the use of personal financial management (PFM) features in banking applications

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Abstract

South African banks have introduced digital financial advice through personal financial management (PFM) features in their bank applications at no additional cost to their customers. In line with existing studies in other regions, usage of PFM features in South Africa remains modest. Drivers of use are largely unknown in the South African context.

The study aims to investigate the factors that influence the intention to use PFM features in banking applications. The TAM extended version of UTAUT2 was used as the framework for this study. Innovativeness, financial knowledge and financial self-efficacy were incorporated into the framework. Collectivism was used to measure how cultural values moderate the role of usage.

The study employed a quantitative approach, utilising a survey to collect data from bank application users working in the financial sector. A total of 273 responses were collected through purposive and snowball sampling and analysed using structured equation modelling and moderation analysis.

The model explained 67% of the intention to use PFM features in banking applications. Attitude had the strongest direct impact on the intention to use PFM features, followed by performance expectancy and social influence. Innovativeness had a mild effect on the intention to use PFM features, while financial self-efficacy positively influenced effort expectancy. Hedonic motivation and trust improved the explanatory power of the model but did not directly impact usage. Collectivism did not have a moderating effect in this research.

The study contributes to the existing literature by providing a South African perspective on PFM adoption and offers banks levers to improve usage.

KEYWORDS

UTAUT-TAM, Hofstede Framework, digital adoption, personal financial management (PFM)

Declaration

I, Bruno Mubanga Ching'andu, 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: Signature:

Signed at ……………………………………………………………

On the 8 …………………………….. day of July ………………………… 2025

Dedication

For Intanda and Mapalo. Thank you for being the bright star that lights up the dark times and being my constant reminder that I am blessed beyond measure. I will always work to earn my most precious title…. Dad

Acknowledgment

My heartfelt thanks to Dr Chiedza Ndlovu. Your guidance in the research has been invaluable. Thank you for your patience and for always making yourself available, despite your hectic schedule.

My work team and colleagues, I was able to manage this process because you were able to pick up the slack at the office. I will always be grateful for your support.

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My father and siblings. Many times, I feel the confidence you have in me is misplaced. Hopefully, this will not be a time my inner critic is right. Your support has been the fuel that has driven me. Thank you.

Zee, you have been a pillar along this journey. I am very aware of the toll this took on you to keep our family afloat. Sincerely, from the bottom of my heart, I am grateful.

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AI: Artificial intelligence

AMOS: Analysis of Moment Structures

AVE: Average variance extracted

CB SEM: Covariance-based structured equation model

eWOM: electronic word of mouth

FSCA: Financial Sector Conduct Authority

PFM: Personal financial management

SPSS: Statistical Package for the Social Sciences

TAM: Technology acceptance model

TPB: Theory of Planned Behaviour

TRA: Theory of reasoned action

UTAUT: Unified theory of adoption and use of technology

CHAPTER 1. INTRODUCTION

1.1 Statement of Purpose

Several authors have postulated that FinTech and the digitisation of financial services are key enablers for financial inclusion (Shiau et al., 2020; Zalan & Toufaily, 2017). However, not all digitised financial products and services are being taken up by users. The digital adoption of financial services and products has varied across sub-Saharan Africa (Hammerschlag et al., 2020). One digitised service that has been introduced to South African consumers is personal finance management applications. Personal finance money tools are digital applications that help users meet their financial goals by assisting them in making decisions about saving, investing, spending, and protecting wealth (Wu et al., 2022). South African banks have introduced personal financial management features and made them available to their customers at no additional cost. Little is known about what drives the use of these features in South Africa.

The adoption of technology in financial services has been researched across different regions, leveraging various established frameworks. Many authors have utilised the Unified Theory of Acceptance and Use of Technology (UTAUT) to explain the adoption of mobile banking (Souiden et al., 2021). Khalilzadeh et al. (2017) extended the UTAUT framework by incorporating constructs of attitude toward technology and self-efficacy from the Technology Acceptance Model (TAM). Other variables included were trust, security, and risk, and the resulting model was found to have high explanatory power of FinTech adoption (Khalilzadeh et al., 2017). This model combines users' perceptions of technology, such as ease of use, perceived utilitarian and hedonic performance, risk, security, and attitude towards technology, with self-efficacy, an individual attribute used to measure adoption (Khalilzadeh et al., 2017). Additional individual attributes such as financial knowledge and perceived innovativeness have also been found to influence the intended use of technology (Bouteraa et al., 2023; Putri & Novia, 2021; Sabir et al., 2023).

Cultural values have also been found to influence the use of technology. Hofstede (2011) assesses cultural values at a country level using the following dimensions: power distance, uncertainty avoidance, individualism versus collectivism, masculinity versus femininity, short-term orientation versus long-term orientation, and indulgence versus restraint.

Hofstede's national cultural values have also been used at an individual level to assess the adoption of technology (Bommer et al., 2022). This study aims to investigate the drivers of personal financial management feature usage in banking applications by examining users' perceptions of the technology, their self-perceptions, and their cultural values.

The research was a cross-sectional quantitative study of South African users of banking applications to explore the drivers of adoption and use of personal financial management features provided in banking apps. Findings shed light on the drivers of adoption and how cultural values impact them.

1.2 Background of the Study

Globally, financial institutions have made great strides in digitising their services. This was accelerated during the COVID-19 lockdowns, which necessitated online interactions with banks to limit movement and contact (Gan et al., 2021). External shocks such as COVID-19 were seen to increase the use of mobile money services across sub-Saharan Africa (Koomson et al., 2021). Such shocks can result in more adoption and use of digital channels and products across banks (Saprikis et al., 2022).

Financial products are becoming increasingly complex, prompting institutions to develop financial management tools, such as Robo-Advisors, and make them accessible to everyone (Khan et al., 2023). The advancement of artificial intelligence has increased organisations' ability to leverage data to transform industries (Ashrafi, 2023). Users can provide companies with information about their financial goals, and data can be leveraged to provide advice based on robotics and analytics (Ashrafi, 2023; Roh et al., 2023).

The limited human involvement reduces the emotional biases in financial advice (Gan et al., 2021). Robo-advisors also mitigate exposure to corrupt security traders and insider trading (Yeh et al., 2023). This digitised financial management tool enables financial education to be done at a scale that increases the reach of the advice with minimal marginal cost (Ashrafi, 2023).

Many banks and investment firms have introduced personal financial management features to provide financial services and advice remotely (Gan et al., 2021; Roh et al., 2023). However, the use of these tools is low in some regions (Khan et al., 2023).

Four of the major banks in South Africa have developed financial tools in their apps for their clients (Bank, 2024; Capitec, 2022; FNB, 2024; Nedbank, 2024). Fintech companies like 22Seven have also been introduced to provide consumers with a single view of their finances across institutions and provide users with holistic advice (22Seven, 2024). Although South African banks have added these to their banking apps, evidence suggests that their usage remains low (FNB, 2022b). Furthermore, the drivers of adoption and use of these tools in the South African context are unexplored.

A key question for banks before investing money in developing these solutions is whether their customers will actually use the technology. Understanding the intention to use personal financial management tools in banking applications is the first step in determining how customers react to them.

1.3 Research Problem

Understanding the drivers of adoption can shed light on how banks can improve the adoption of these tools. The literature reviewed shows that perceptions about FinTech performance, ease of use, and hedonic value influence its adoption (Khalilzadeh et al., 2017).

Some authors have argued that users' perceptions influence the adoption of FinTech (Alkhwaldi et al., 2022; Bouteraa et al., 2023; Putri & Novia, 2021; Sabir et al., 2023). Aspects such as individuals' self-efficacy, claimed financial literacy, and perceived innovativeness have been found to influence the adoption (Alkhwaldi et al., 2022; Khalilzadeh et al., 2017; Wu & Liu, 2023).

The literature also shows how some cultural dimensions have a moderating effect on the factors that drive adoption and explains differences across countries (Wu & Liu, 2023). Individual-level cultural values have also been found to moderate adoption drivers (Kurniasari et al., 2022).

This study examines the identified factors that drive the use of technology in relation to personal financial management features in banking apps in South Africa. It examines how perceptions of these features, self-perceptions, and cultural values influence the use of personal financial management features in bank apps.

1.4 Research Questions

This study examined the factors influencing the use of personal financial management features among bank app users in South Africa. The research examines how perceptions of the technology, individual attributes, and culture impact the adoption of personal financial management tools in banking applications. The following are the research questions:

1. Do users' individual attributes play a role in the adoption and use of the banking apps' personal financial management features?

2. Do users' perceptions of their banks' personal financial management features influence the adoption and use of these features?
3. Do individual cultural values influence attitudes toward personal financial management features in banking apps?

1.5 Rationale

With advancements in AI and an increase in the volume and variety of data, the ability to provide meaningful financial education has also increased. Many South African banks have included personal financial management tools in their applications. This means that consumers with internet access can receive financial guidance directly through their banking apps.

The low usage of these tools has been noted across financial services providers. FNB, one of the biggest banks in South Africa, reportedly has over 5 million app users, with only 200 000 using budgeting features (FNB, 2022a, 2022b). This means only 4% of FNB banking customers use the features, although these are used for free. Understanding the drivers of intention to use these features is crucial to increasing their adoption.

This study contributes to the existing body of literature on digitised financial services and FinTech adoption in the following ways:

1. Identifying factors that drive bank customers' intention to use personal financial management tools in banking applications in the South African context.
2. Build an explanatory model to predict the usage of personal financial management features in banking applications
3. Answering how individual attributes play a role in FinTech adoption
4. Assess how cultural values impact the digital adoption of digitised financial services.

The findings have implications for independent FinTech organisations and banks seeking to enhance their customers' financial well-being by offering them meaningful financial education. Policy makers can also use these insights when assessing the performance of digitised financial education provided by banks. The research will also add to the existing body of knowledge on personal financial management usage in the African context.

1.6 Delimitations of the Study

The research focused on South African consumers who have banking applications. Cultural values were measured at an individual level. The adoption of financial services was limited to the integration of personal financial management features in bank apps, thereby excluding standalone applications from non-banks. Other financial products and services were out of the scope of this study.

1.7 Definition of Terms

Banking app – applications designed by banks to allow users to use financial services via a cell phone or an internet browser.

PFM – Personal financial management application that provides advice or helps users manage their finances, including budgeting, investing, saving and protecting wealth.

FinTech – shortened form for financial technology. For the purpose of the study, it refers to non-bank firms using technology to provide financial services.

1.8 Assumptions

Observations in this study were independent of one another, and none of the individual responses influenced any other. The sample achieved was representative of bank customers who work in the financial services sector.

Responses to questions are assumed to be truthful and honest reflections of their perspectives.

CHAPTER 2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1 Introduction

This section of the study reviews the literature on digital adoption and the use of technology, as well as how culture influences it. The section outlines the theoretical frameworks used for the study.

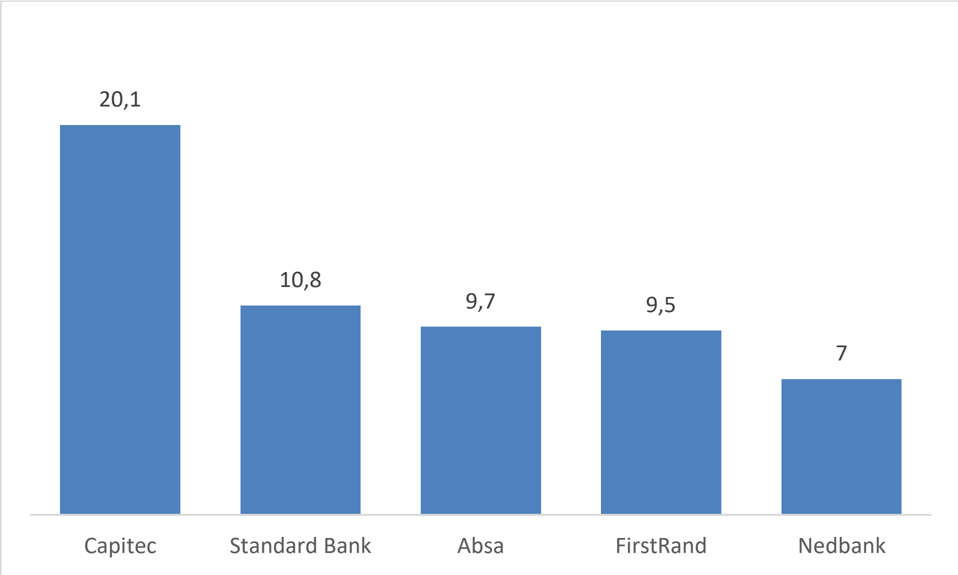
The literature identified explores users' adoption of financial services and unpacks the cultural impact on adoption in multiple contexts and regions, most of which are not in South Africa.

The section begins by providing an overview of the South African banking landscape and then explores theories of digital adoption. The chapter proceeds to unpack the cultural values used in this study. It further explores what literature has revealed regarding adoption in financial services, including PFM features. The next section focuses on how self-perceptions have moderated the adoption of technology and how cultural values have been found to influence its use. The chapter concludes with a suggested framework for this study based on the identified literature.

2.2 South African Banking Landscape

Five banks, namely First Rand, Standard Bank, ABSA, Nedbank, and Capitec, dominate the South African banking sector. They all have applications that their customers use to access products and services (BusinessTech, 2023) .

Figure 1: Number of customers by bank



Source: BusinessTech (2023)

The market has recently seen the introduction of digital banks that challenge these established banks and eat into their market share. Tymebank and Discovery Bank have been the most successful, with 8.5 million clients and 700 000, respectively, and the former reached profitability in a short four-year period (Theunissen, 2024). Both of these digital banks have included PFM features in their applications to attract clients (Mannweiler, 2024; Tymebank, 2019). These applications utilise data to assist their clients in making informed financial decisions.

South African consumers are under increasing pressure to manage inflation and rising interest rates (Opperman, 2023). Most South African banks have introduced digital personal financial management features in their apps to ensure that financial advice reaches their customer base (Bank, 2024; FNB, 2024; Nedbank, 2024).

2.3 Digital Adoption Theory

As digitisation intensifies across industries, its adoption has become a popular research topic for authors. The theory of reasoned action (TRA) was one of the earlier adoption theories and focused on the relationship between people's attitudes and behaviour (Fishbein & Ajzen, 1974). The theory of planned behaviour (TPB) included time and place to TRA dimensions hence bringing in context and individuals' ability to exert self-control (Ajzen & Fishbein, 1977). However, neither of the initial theories addressed the adoption of technology specifically.

The technology acceptance model (TAM) was built off the foundation of TRA and TPB specifically to shed light on how technology is accepted (Davis et al., 1989). The framework included perceived usefulness and ease of use to explain the adoption of technology (Davis et al., 1989). Later versions incorporated aspects such as social influence and other cognitive instrumental processes to refine the initial model. However, the framework was mostly suited to explaining adoption in an organisational context.

Venkatesh et al. (2003) conducted a comprehensive synthesis of the existing models to develop the Unified Theory of Acceptance and Use of Technology (UTAUT). The initial UTAUT theory focused on how four dimensions (Performance expectancy, effort expectancy, social influence, and facilitating conditions) drive usage behaviour. However, just like TAM, UTAUT was still focused on an organisational context. Venkatesh et al. (2012) extended the model to include dimensions of price, hedonic motivation, and habit that are more relevant to individuals resulting in UTAUT2.

Additional dimensions of attitude, self-efficacy, risk, security, and trust were included in the model to explain the drivers of adoption in the financial services context (Khalilzadeh et al., 2017). These attributes, which integrate UTAUT with TAM, resulted in the UTAUT-TAM model, which was found to have 20% greater explanatory power and accuracy in the adoption of mobile payments than the original UTAUT (Khalilzadeh et al., 2017).

2.4 Cultural Values (Hofstede's Cultural Dimensions Theory)

Culture is defined as a collective mental programming shared by some and not all people, and it distinguishes one group from another (Hofstede, 1980). Hofstede's national culture theory uses six dimensions, namely individualism versus collectivism, masculinity versus femininity, long-term versus short-term orientation, indulgence versus restraint, uncertainty avoidance and power distance (Hofstede, 2011).

The initial theory had four factors, namely individualism vs collectivism, masculinity vs femininity, uncertainty avoidance and power distance (Hofstede, 1980). A study across 40 countries in which IBM operated identified significant differences in employee behaviour across the four cultural dimensions (Hofstede, 1980).

- **Individualism versus collectivism** looks at how people value relationships with others as opposed to individual rights and achievements (Hofstede, 1980). Collectivist cultures tend to favour groups and loyalty (Hofstede, 1980). Individualistic cultures place more importance on personal goals and tend to favour more direct communication than collectivist cultures (Hofstede, 1980).
- **Masculinity versus femininity** looks at how societies view traditionally masculine values like assertiveness and competition as opposed to traditionally feminine attributes such as nurturing, quality of life, and cooperation (Hofstede, 1980).
- **Uncertainty avoidance** looks at how people in a society cope with ambiguity and uncertainty (Hofstede, 1980). Individuals and societies with high uncertainty avoidance tend to be more resistant to change and risk-taking (Hofstede, 1980).

- **Power distance** looks at the extent to which people accept or expect power to be distributed unequally (Hofstede, 1980). Individuals in societies with high degrees of power distance tend to accept hierarchies, while those in low power distance societies expect a more consultative approach (Hofstede, 1980).

Additional studies were conducted, leading to the discovery of the fifth dimension, long-term orientation (Hofstede & Minkov, 2010).

- **Short-term versus long-term orientation** refers to the degree to which individuals can delay gratification (Hofstede & Minkov, 2010). Individuals in long-term oriented societies tend to be more persistent and emphasise long-term savings (Hofstede & Minkov, 2010). Short-term societies favour short-term gratification and prioritise the present (Hofstede & Minkov, 2010).

The sixth and final dimension of cultural values was:

- **Indulgence versus restraint, which** looks at societal impulse and desire control (Hofstede, 2011). High-restraint societies tend to suppress gratification by conforming to social norms. Indulgent societies allow free gratification and tend to spend more on luxuries, while restrained societies tend to spend on practical things and save more (Hofstede, 2011).

2.5 Culture and Digital Adoption in Financial Services

The adoption rates of digitised financial services have varied by service and region for various reasons. It has been found that cultural values have an impact on the levels of financial inclusion and adoption of digital financial services (Wu & Liu, 2023).

Individualistic cultures tend to have a higher adoption of digital banking due to their lower reliance on community support (Kumar et al., 2021; Kurniasari et al., 2022; Lu et al., 2021; Merhi & Indiana University South, 2021). However, Kumar et al. (2021) found that individualism did not significantly influence the adoption of mobile payments among consumers in China and India. However, they found that adoption by retailers was significantly influenced by individualism (Kumar et al., 2021). Similar findings have been reported regarding the lack of significance of individualism in the adoption of mobile banking in Brazil, India, and the UK (Picoto & Pinto, 2021).

High power distance has been found to increase the use and adoption of digitised financial services across multiple countries (Picoto & Pinto, 2021). There was a similar finding in countries showing high power distance directly influences the adoption of e-commerce authority of the platform (Merhi & Indiana University South, 2021). Recent graduates in Indonesia who value power distance were more likely to adopt digital payments as authority is passed to the institution (Kurniasari et al., 2022).

Uncertainty avoidance influences consumers' adoption of digitised financial services, and it was found to have a weak impact on the adoption of electronic wallets (Bommer et al., 2022). Mobile payment platform adoption across China, Belgium, the USA, and Indonesia was not significantly impacted by uncertainty avoidance (Kurniasari et al., 2022; Wu & Liu, 2023). Merhi and Indiana University South (2021) found that uncertainty avoidance did not influence the adoption of e-commerce across 60 countries.

Kumar et al. (2021) found that long-termism had a positive impact on SMEs and retailers, but not on individuals, in the adoption of FinTech payments. Studies in e-commerce also found it to be insignificant in influencing adoption by consumers (Merhi & Indiana University South, 2021). However, Picoto and Pinto (2021) found that long-term-oriented cultures have a positive impact on the adoption of mobile banking. Long-term-oriented cultures were also found to positively influence the adoption of digital currencies (Luu et al., 2023).

Masculine cultural values were found to have higher rates of adoption by institutions (Luu et al., 2023). This dimension has also been found to be insignificant for consumers in the adoption of e-commerce (Merhi & Indiana University South, 2021).

Indulgence was found to have a positive effect on the adoption of e-commerce (Merhi & Indiana University South, 2021).

2.6 Digital Adoption in Financial Services

A meta-analysis study found that all constructs in UTAUT 2 significantly influence the behavioural intention to use e-wallets (Bommer et al., 2022). The study further identified price, hedonic motivation, and facilitating conditions as having the strongest relationship with the intention to use e-wallets (Bommer et al., 2022).

Furthermore, Gan et al. (2021) found that performance expectancy has a positive influence on the intention to adopt financial Robo-advisors in Malaysia. However, a study in India on the use of budgeting features found it insignificant in driving the intention to use them (Savitha & Hawaldar, 2022).

Moreover, social influence was found not to have an effect on the adoption of electronic banking in Sweden (Abikari et al., 2023). Similar findings were made in the UAE about FinTech adoption (Bouteraa et al., 2023). However, social influence was found to be significant in the context of the adoption of Robo-advisors in China and Taiwan (Roh et al., 2023; Yeh et al., 2023).

Facilitating conditions were found to impact existing users differently from new users of mobile banking apps (Saprikis et al., 2022). Existing users of banking apps were more likely to know the requirements of using the app; therefore, facilitating conditions influenced the behavioural intention to continue using the app (Saprikis et al., 2022). However, in the same study, facilitating conditions did not influence non-users' behavioural intentions (Saprikis et al., 2022). Also, it was found that facilitating conditions did not influence the actual use of mobile banking in India (Kumar et al., 2023). Furthermore, Gan et al. (2021) found that facilitating conditions did not influence the adoption of Robo-advisors in Malaysia.

Hedonic motivation has had mixed results in influencing the intention to use mobile banking services (Wu & Liu, 2023). Studies have found it to positively correlate with perceived value, but not the intention to use Robo-advisory services (Ashrafi, 2023).

Kumar et al. (2023) found that price value did not influence the adoption of mobile banking in India. However, it significantly impacted the adoption of FinTech services in the UAE (Bouteraa et al., 2023).

Wu and Liu (2023) found that habit has a positive influence on the intention to use mobile payments. Habits were found to drive actual usage of mobile payments in China, but were insignificant in Belgium and the US (Wu & Liu, 2023). However, Gan et al. (2021) found that the tendency to rely on Robo-advisors positively influenced the behavioural intention to use them. There were similar findings that showed that customer engagement significantly influenced the intention to use budgeting applications (Savitha & Hawaldar, 2022).

In China and India, effort expectancy significantly contributed to the intention to adopt FinTech and digital financial services (Kumar et al., 2023; Sabir et al., 2023). However, findings in Greece and the UAE found that effort expectancy does not influence the adoption of banking apps (Bouteraa et al., 2023; Saprikis et al., 2022).

Researchers have found that attitudes towards technology greatly impact the adoption of technology (Khalilzadeh et al., 2017; Roh et al., 2023; Yi et al., 2023). Roh et al. (2023) combined UTAUT and TRA to explore the adoption and psychological factors in attitudes towards Robo-advisors. Findings showed that attitude towards Robo-advisors mediated perceived benefit, effort, facilitating conditions, and social influence (Roh et al., 2023). In this study, perceived security did not show a significant impact on attitude towards Robo-advisors (Roh et al., 2023).

2.7 Individual Attributes and Adoption

Factors other than perceptions of technology need to be addressed to increase the use of FinTech. Individual factors have also been found to impact the adoption of technology and FinTech.

Multiple authors have found that the innovativeness of users drives adoption (Bouteraa et al., 2023; Putri & Novia, 2021; Sabir et al., 2023). The optimism and innovativeness of individuals in China had a positive effect on FinTech adoption (Sabir et al., 2023). Perceived innovativeness of the individual had a significant impact on behavioural intention to use mobile payments in China, the USA, and Belgium (Wu & Liu, 2023).

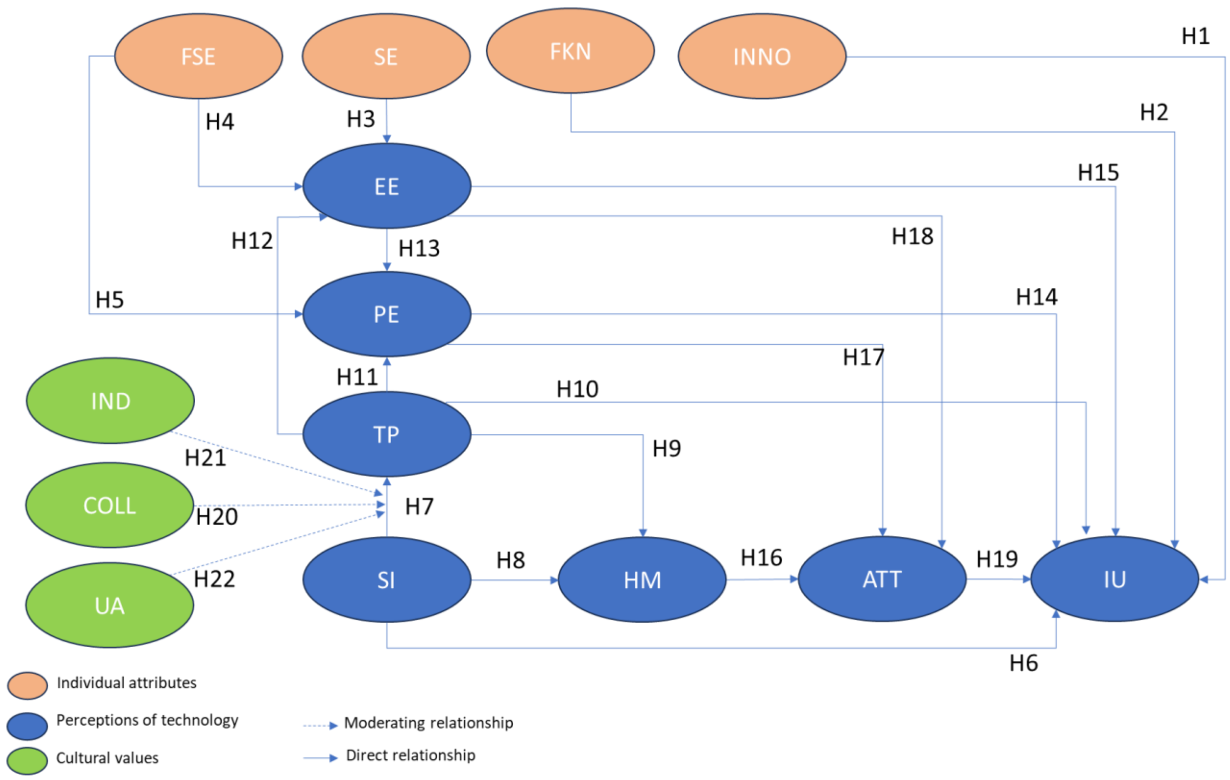
Levels of financial literacy did not contribute to FinTech adoption (Sabir et al., 2023). However, some authors found that financial knowledge significantly influences adoption (Yi et al., 2023). Self-efficacy was also found to significantly influence the intention to use budgeting applications (Savitha & Hawaldar, 2022).

Self-efficacy has positively contributed to the understanding of the adoption of financial technology. Researchers have found it to influence perceived usefulness and effort expectancy in digital payments and Robo-advisory FinTech (Khalilzadeh et al., 2017; Shiau et al., 2020). Shiau et al. (2020) distinguish between financial self-efficacy and technological self-efficacy in the context of wealth management applications. They found it to positively impact users' perceptions of usefulness (Shiau et al., 2020).

2.8 Analytical Framework

The following framework was developed in line with the literature to address the research questions. It was built upon UTAUT-TAM as a foundation and included individual attributes identified in the literature to impact the adoption of FinTech.

Figure 2: Theoretical model and hypotheses



Source: Author's own compilation

Constructs from UTAUT-TAM were used as variables to measure users' perceptions of technology. The extended version was found to increase the explanatory power of the model by including self-efficacy and attitude to UTAUT variables in a sequential framework using attitude as a mediating construct (Khalilzadeh et al., 2017). Attitude fully mediated the relationship between behavioural intention to use and hedonic performance, as well as performance expectancy (Khalilzadeh et al., 2017).

The individual attributes assessed in this research included perceived innovativeness, financial knowledge, financial self-efficacy, and self-efficacy. Individual attributes have been found to contribute to the adoption of technology. The preceding literature also found that perceived innovativeness positively influences the adoption of Robo-advisory services (Alkhwaldi et al., 2022; Bouteraa et al., 2023; Putri & Novia, 2021; Sabir et al., 2023).

Innovativeness was found to positively moderate effort expectancy and attitude towards Robo-advisors. (Sabir et al., 2023). Ashrafi (2023) also found that perceived innovativeness had a direct impact on the adoption of Robo-advisory. As such, the following hypothesis was developed regarding innovativeness and personal financial management tools in banking applications:

> *H1: Innovativeness positively impacts intention to use PFM features in banking apps.*

It was found that financial literacy does not affect the adoption of FinTech in Jordan (Alkhwaldi et al., 2022). However, financial knowledge was found to positively influence willingness to adopt Robo-advisory services (Yi et al., 2023). As a result, the following hypothesis was developed:

> *H2: Financial knowledge has a positive impact on the intention to use PFM features in banking applications.*

Khalilzadeh et al. (2017) found that self-efficacy positively impacted the effort expectancy of users of near-field communications (NFC) payments. Shiau et al. (2020) split this construct into financial self-efficacy and technological self-efficacy in the context of wealth management applications and found that they positively impacted perceived usefulness. It was also found that financial self-efficacy positively impacted the perceived usefulness of wealth advisory applications. This resulted in the following hypotheses concerning personal attributes:

> *H3: Self-efficacy is positively related to effort expectancy PFM features in mobile banking apps.*

> *H4: Financial self-efficacy is positively related to effort expectancy of PFM features in mobile banking apps.*

> *H5: Financial self-efficacy is positively related to performance expectancy of PFM features in mobile banking apps.*

The identified individual attributes were all exogenous variables that were not influenced by any other. Perceptions of technology were predominantly assessed using constructs from the UTAUT2 model. Attitude was also included in TAM.

Another exogenous variable in the framework was social influence. Social influence had a direct and positive impact on the adoption of digital banking among users (Windasari et al., 2022). Due to the direct impact of these variables on the intention to use FinTech, the following hypotheses were developed:

> *H6: Social influence is positively related to intention towards using PFM features in banking apps.*

Social influence has been found to correlate positively with trust in technology (Khalilzadeh et al., 2017). Khalilzadeh et al. (2017) found that social influence has a strong impact on trust in digital payment technology. This resulted in the following hypothesis:

> *H7: Social influence positively impacts trust in PFM features in mobile banking apps.*

Khalilzadeh et al. (2017) found that trust in NFC payments has a positive impact on hedonic motivation. They also found that social influence is a strong driver of hedonic motivation in the context of NFC payments (Khalilzadeh et al., 2017). This resulted in the following hypotheses:

H8: Social influence is positively related to hedonic motivation towards PFM features in mobile banking apps.

H9: Trust in PFM features in banking applications positively related to hedonic motivation towards PFM features in mobile banking apps.

Trust in technology has also been found to directly influence behavioural intention to use FinTech management applications (Kumar et al., 2023; Roh et al., 2023; Yeh et al., 2023; Yi et al., 2023). Khalilzadeh et al. (2017) also found that trust in NFC payments had a positive impact on performance expectancy. They also found that trust has a direct positive effect on effort expectancy. Effort expectancy, in turn, positively impacted performance expectancy. As a result, the following hypotheses were included in the framework:

H10: Trust in PFM features in banking apps is positively related to the intention to use PFM features in banking apps.

H11: Trust in PFM features in banking apps is positively related to the performance expectancy of PFM features in banking apps.

H12: Trust in PFM features in banking apps is positively related to effort expectancy of PFM features in banking apps.

H13: Effort expectancy positively related to performance expectancy of PFM features in banking apps.

More original UTAUT2 constructs have also been found to directly impact the adoption of Robo-advisory in the FinTech context (Nain & Rajan, 2024). Wu et al. (2022) found that performance expectancy had the strongest direct impact on the use of digital finance tools in China. Ease of use significantly impacted the intention to use personal financial management services (Walsh & Lim, 2020).

H14: Performance expectancy is positively related to the intention to use PFM features in banking apps.

H15: Effort expectancy is positively related to the intention to use PFM features in banking apps.

Performance expectancy, effort expectancy, and hedonic motivation have also been found to positively impact attitudes towards financial management tools like Robo-advisors (Yeh et al., 2023). This results in the following hypotheses to test these constructs regarding their impact on attitudes towards PFM features in banking applications.

H16: Hedonic performance is positively related to attitude towards PFM features in mobile banking apps.

H17: Performance expectancy is positively related to users' attitudes towards PFM features in mobile banking apps.

H18: Effort expectancy is positively related to attitude towards PFM features in mobile banking apps.

Attitude towards PFM refers to users' positive feelings towards PFM in banking applications. Researchers have found attitude to have the strongest direct impact on intention to use financial service technology (Roh et al., 2023; Yeh et al., 2023). This led to the formulation of the first hypothesis for this study.

H19: Attitude towards using PFM features in banking apps is positively related to the intention to use PFM features in banking apps.

Kumar et al. (2023) found that price did not influence the adoption of mobile financial services; therefore, it was removed from the framework. Facilitating conditions are insignificant for non-users of technology, likely due to their unfamiliarity with the requirements (Saprikis et al., 2022). The perceived security of Robo-advisors did not influence the attitude or use of Robo-advisors, and therefore, it was excluded from the framework (Roh et al., 2023; Yeh et al., 2023).

Price value and facilitating conditions will be excluded from the UTAUT 2 constructs used in this framework.

Since existing users are likely to be content with the existing security for banking, security and risk will also be excluded. It was found that facilitating conditions did not have an impact on the intention to use FinTech (Khalilzadeh et al., 2017). As such, facilitating conditions will also be excluded as a variable for this study.

In multiple studies, constructs in Hofstede's cultural dimensions have been found to influence FinTech adoption (Kotkowski, 2023; Luu et al., 2023; Picoto & Pinto, 2021; Wu & Liu, 2023; Zalan & Toufaily, 2017). Literature reveals that cultural values play a role in individuals' trust in digital financial services. Long-term orientation and masculinity have not been found to influence the adoption of financial services and e-commerce (Kumar et al., 2021; Merhi & Indiana University South, 2021). These will also be excluded from the framework.

Individualism and power distance have both been found to positively moderate social influence and trust in digital payments (Kurniasari et al., 2022; Luu et al., 2023; Picoto & Pinto, 2021). Uncertainty avoidance moderates financial conditions and actual use (Luu et al., 2023). Bommer et al. (2022) found that indulgence had a significant but weak moderation effect on social influence and the adoption of e-wallets. However, this has not been tested in the context of PFM. The following hypotheses were developed for the cultural impacts on the use of PFM features in banking apps.

> *H20: Collectivism negatively moderates social influence and trust in PFM features in banking apps.*

> *H21: Indulgence moderates social influence and trust in PFM features in banking apps.*

> *H22: Uncertainty avoidance positively moderates social influence and trust in PFM features in banking apps.*

2.9 Conclusion of Literature Review

This chapter unpacked theoretical frameworks on adoption and culture. Literature on the adoption of digital financial services and PFM tools was then used to show key drivers across different types of solutions. The cultural impact on adoption was then unpacked, showing that some dimensions have a significant impact on usage.

Finally, a framework and hypotheses were formulated based on the literature. Individual attributes were all exogenous variables. Social influence was the only exogenous variable of the original UTAUT2 constructs. All other constructs were both endogenous and exogenous, except intention to use, as it was the final dependent variable in the model. Three cultural values have also been included as moderators in the model.

These constructs have been used to develop a model to explain the intention to use personal financial management tools in banking applications in South Africa.

CHAPTER 3. RESEARCH METHODOLOGY

This section describes the methodology used to answer the research questions and fulfil the objectives of this study. It includes the approach, design, sample description, and survey design. The chapter describes how data was collected and analysed, including quality assurance. It concludes by highlighting ethical considerations and proposed timelines.

3.1 Research Approach

The study seeks to explore how identified factors influence the intention to use PFM features in bank apps. These factors are in three dimensions, namely perception of technology, individual attributes, and cultural values.

This research was a cross-sectional, quantitative explanatory study due to its ability to explain relationships between variables (Saunders & Lewis, 2012). A similar approach was used in understanding the drivers of the use of PFM tools in rural China (Wu et al., 2022). A quantitative approach also allows for findings in a statistically significant sample to be generalised to the population (Saunders & Lewis, 2012).

Typically, this approach leverages surveys or experiments to collect data that is analysed using statistical computations (Saunders & Lewis, 2012). In line with this, the study uses surveys to collect data and IBM Statistical Package for Social Sciences (SPSS) and Analysis of Movement Structures (AMOS) statistical analysis and structured equation modelling.

3.2 Research Design

The research employed an online survey to gather perceptions from banking app users. Surveys that ask questions such as “who”, “what”, “where”, and “how much” are used to collect data from clients (Saunders & Lewis, 2012). These types of questions help measure the relationship between variables that potentially influence the adoption of personal financial management features in banking apps. Surveys are a cost-effective way of collecting data from a large group of respondents (Saunders & Lewis, 2012).

Survey questions were used to collect data within the dimensions of research at a specific point in time, making this cross-sectional. Cross-sectional research is an appropriate way to conduct research and get a snapshot of people's perceptions at a particular point in time (Saunders & Lewis, 2012). Many authors in adoption literature have used this design (Sabir et al., 2023).

3.3 Data Collection Methods

A structured questionnaire was designed to collect primary data from respondents. The study used an online survey programmed on Qualtrics and distributed it to individuals through social media platforms and emails. Multiple authors have used online surveys to collect data for adoption studies (Ashrafi, 2023; Wu et al., 2022). Survey questions were in English with clear and concise language. Non-probability purposive sampling was used to obtain the sample.

3.4 Population and Sample

The study focused on the use of personal financial management features in banking apps. The total population in this study was South African bank customers who use banking apps. Results obtained from the respondents were large enough to generalise findings to a broader group (Saunders & Lewis, 2012).

3.4.1 *Population*

The population is defined as the complete set of group members (Saunders & Lewis, 2012). For this study, the population was South African banking app users working in the financial sector.

3.4.2 *Sample and Sampling Method*

Saunders and Lewis (2012) define a sample as a subgroup of an entire population. The method used to obtain the sample for the study was a combination of convenience and snowball sampling. Purposive sampling uses those who are easy to obtain (Saunders & Lewis, 2012). Snowball sampling is a type of non-probabilistic sampling where initial sample members identify and invite subsequent members (Saunders & Lewis, 2012). Yi et al. (2023) used convenience sampling in a study of Robo-advisory adoption among millennials.

Participants were selected to participate only if they were between 18 and 65 years old and used the banking apps of South African banks. The research aimed to obtain a sample size greater than 200 full responses. The Hoelter index showed that a minimum sample size of 198 is adequate to test the model (Khalilzadeh et al., 2017). A similar approach was used to sample participants in an Indian study of Robo-advisory adoption (Ashrafi, 2023). Snowball sampling was used to collect data in a study on e-commerce purchase intention (Al-Adwan et al., 2022)The survey was distributed on the author's social media and contact list, which were easiest to reach. Respondents to this survey were requested to forward the survey to their contacts for additional samples.

3.5 The Research Instrument

A survey was designed by adapting questions from previous literature on adoption within digitised financial services. Understanding perceptions and attitudes of PFM features were addressed using questions from the chosen dimensions in UTAUT-TAM (Khalilzadeh et al., 2017).

Perceived innovativeness was measured using adapted questions from Bouteraa et al. (2023). Financial knowledge indicators were obtained from (Alkhwaldi et al., 2022). Financial self-efficacy questions were adapted from (Shiau et al., 2020)

Hofstede's cultural dimension questions measuring uncertainty avoidance and collectivism versus individualism were derived from (Wu & Liu, 2023). Questions used to measure indulgence versus constraint were taken from (Heydari et al., 2021). The questions used five-point Likert Scale statements to measure respondents' perceptions.

The questionnaire was then split into five main sections. They were (1) the use of personal PFM features in banking apps, (2) individual attributes, (3) perceptions of PFM features (4) individual cultural values, and (5) demographic questions. Details of the questions are shown in Table 3.5.1.

Table 3.5.1 Survey instrument

Construct	Questions on perceptions of the technology	Source
Performance expectancy	• I find PFM features useful in managing my finances. • Using PFM features enables me to accomplish important money management tasks. • Using PFM features helps me manage my finances quickly.	(Khalilzadeh et al., 2017)
Effort expectancy	• Learning how to use PFM features would be easy for me. • It is easy to become skilful at using PFM features. • I would find PFM features easy to use.	Khalilzadeh et al., 2017)
Trust	• I believe PFM keep their promise. • I believe PFM keep customers' interests in mind. • I believe PFM features are trustworthy.	Khalilzadeh et al., 2017)
Hedonic motivation	• Using PFM features would be fun. • Using PFM features would be enjoyable. • Using PFM features would be pleasant.	Khalilzadeh et al., 2017)
Social influence	• People who influence my behaviour think that I should use PFM. • I will use PFM features if my friends use them too. • People who are important to me think that I should use PFM.	Khalilzadeh et al., 2017)
Attitude	• Using PFM to manage finances is a good idea. • Using my bank app PFM features to manage my finances would be pleasant. • I like the idea of using PFM features.	(Khalilzadeh et al., 2017)

Intention to use	• I intend to use PFM features. • I predict that I should use PFM features. • I plan on using PFM features.	(Khalilzadeh et al., 2017)
Construct	**Questions on individual attributes**	**Source**
Self-efficacy	• I could use PFM if only there is a built in-help facility for assistance. • I could use PFM if someone else had helped to get started. • I could use PFM if someone showed me how to do it first.	(Khalilzadeh et al., 2017)
Financial self-efficacy	• I am fully capable of making personal financial decisions. • I am confident in my ability to make personal financial decisions. • I am qualified for the task of making personal financial decisions.	(Shiau et al., 2020)
Perceived innovativeness	• If I hear about new technology, I look for ways to experiment with it. • I am usually the first to try new information technologies among my peers. • I am not hesitant to try out new information technologies. • I like to experiment with new information technologies.	(Bouteraa et al., 2023)
Financial knowledge	• I have knowledge of compounding interest. • I have knowledge of inflation. • I have knowledge of risk diversification.	(Alkhwaldi et al., 2022)
Construct	**Questions on cultural values**	**Source**
Individualism	• Being accepted as a member of a group is more important than having autonomy and independence. • Group success is more important than individual success. • Being loyal to a group is more important than individual gain. • Individual rewards are not as important as group welfare.	(Wu & Liu, 2023)
Indulgence	• There should be limits on individuals' enjoyment. • Societies should value free gratification of desires and feelings. • The gratification of desires should be delayed.	(Heydari et al., 2021)
Uncertainty avoidance	• Order and structure are very important in society. • It is better to have a bad situation that you know about than to have an uncertain situation which might be better.	(Wu & Liu, 2023)

	• People should keep things the same because things could get worse.	

3.6 Procedure for Data Collection

The Qualtrics survey was distributed via email and various social media platforms using a link. The platforms were LinkedIn and WhatsApp. Yi et al. (2023) used social media to obtain data in their study on Robo-advisory usage among millennials. In addition, respondents were asked to forward the link to others who use banking apps.

3.7 Data Analysis Strategies and Interpretation

Data collected from the survey was analysed using IBM SPSS and AMOS packages. Demographic data was used for the descriptive statistics to describe the sample. Relationships between constructs will be used to develop a model that will be tested to explain the intention to use PFM features in banking applications.

Authors have used structural equation modelling (SEM) to test hypotheses in proposed models (Sabir et al., 2023). SEM was used to measure this model's hypotheses.

Researchers tested the measurement model with known model fit indices (Hair & Sarstedt, 2019). A structural model was drawn in line with the hypotheses. This model was used to test the hypothesised relationship and assess how well the framework explains the intention to use PFM features in banking applications. Yi et al. (2023) used this method in their study on Robo-advisory. Moderation analysis of the cultural value dimensions was also conducted to measure the moderating effect on hypothesised relationships.

3.8 Possible Limitations and Challenges of the Study

Convenience sampling results in a response bias as only those who are interested in the survey and have time will complete it. The findings from this study were limited to the population of banking app users working in the financial sector. These might differ from the general population.

Respondents who are not comfortable reading English may not have understood some of the questions. Excluded constructs from UTAUT-TAM or Hofstede’s cultural dimensions might be more significant in influencing the adoption and use of PFM features in banking apps.

3.9 Quality Assurance

The quality of the research was measured to ensure the validity and reliability of the data. The measurement model was tested for model fit before assessing relationships between variables. Data quality checks were done to exclude responses from low-engagement participants. This included responses with more than two missing values and a standard deviation below 0.25. The remaining missing values were checked and were found to be random. These missing values were imputed using the linear interpolation method.

3.9.1 *External Validity OR Transferability*

External validity relates to how the results of a study based on a sample can explain or be generalised to the population (Saunders & Lewis, 2012). The collection might introduce bias as it was based on the researchers’ network.

The results of the study might not be generalisable outside South Africa or to stand-alone PFM apps that are not provided by a bank. Caution must be applied when generalising the findings to a broader population of individuals working outside the financial sector.

3.9.2 *Internal Validity OR Credibility*

To ensure internal validity, the variables of this study were derived from UTAUT-TAM and Hofstede’s cultural dimensions theory (Hofstede, 2011). A pilot survey was sent to a small number of respondents to check for understanding and flow. Early in the survey, the questionnaire used screening questions to eliminate individuals who did not use banking apps.

The data from the indicators was tested for internal validity using average variance extracted (AVE) to test how well they explained the unobserved constructs(Fornell & Larcker, 1981). Discriminant validity tests were also conducted, comparing AVE with squared correlations of all variables to ensure each construct was independent of the other (Fornell & Larcker, 1981).

3.9.3 *Reliability OR Dependability*

Reliability of research refers to how repeatable results are (Saunders & Lewis, 2012). Items in this study were tested using Cronbach’s alpha. The ranges used for this study were between 0.7 and 0.9 (Fornell & Larcker, 1981). Sabir et al. (2023) used this method dimensions in their study on Robo-advisory usage.

3.10 Ethical Considerations

The questionnaire asked participants to provide information based on their perceptions and daily lives. Minimal demographic information was used for statistical purposes. No data identifying respondents was collected. This ensured the confidentiality of participants.

No participants were coerced into filling in the survey. The sample was based on individuals employed in the financial sector who use banking apps, and no vulnerable groups were specifically targeted. Demographic questions were used to exclude minors and non-banking app users from completing the survey. Data was stored in a password-encrypted file for additional security.

CHAPTER 4. DATA ANALYSIS

This chapter discusses the analysis of the data collected using the methodology and instrument outlined in Chapter 3. It begins with descriptive statistics of the respondents to shed light on the participants in this study. Descriptive statistics of the variables follow to understand central tendency and dispersion using means and standard deviation. A correlation analysis of all variables will follow this.

Normality testing using skewness and kurtosis will be introduced next, followed by the analysis of the model. Results from the reliability analysis and internal and discriminate validity of all constructs in the study will also be shared. The model results will be preceded by the measurement model before the structural model. Finally, the results of the moderators identified in the literature will be provided. The chapter concludes with a summary and highlights of the key points to be discussed. Contracts used in this study were coded for simplicity in SPSS and AMOS. Table 3.10.1 shows all the variables in this study and their associated codes.

Table 3.10.1 Variable codes

Dimension	Variable name	Code	Type
Perceptions of technology	Performance expectancy	PE	Endogenous
	Effort expectancy	EE	Endogenous
	Social influence	SI	Exogenous
	Hedonic motivation	HM	Endogenous
	Trust in PFM	TP	Endogenous
	Attitude	ATT	Endogenous
	Intention to use	IU	Endogenous
Individual attributes	Self-efficacy	SE	Exogenous
	Financial self-efficacy	FSE	Exogenous
	Financial knowledge	FKN	Exogenous
	Innovativeness	INNO	Exogenous
Cultural values	Collectivism	COLL	Moderator
	Uncertainty avoidance	UA	Moderator
	Indulgence	IND	Moderator

Source: Author's own compilation

4.1 Descriptive Statistics

The demographic statistics of the study participants are outlined in Table 4.1.1. These include age, gender, income, and banking apps used.

Table 4.1.1 Demographic statistics

Characteristics		Frequency	Percent
Gender	Female	174	63,7
	Male	97	35,5
	Prefer not to say	2	0,7
Race	Black (African)	130	47,6
	White	81	29,7
	Indian (Asian)	33	12,1
	Coloured	21	7,7
	Prefer not to say	8	2,9
Age	20 – 25	9	3,3
	26 – 35	54	19,8
	36 – 45	113	41,4
	46 – 55	78	28,6
	56 – 65	19	7,0
Education	Matric	20	7,3
	Diploma	66	24,2
	Degree	61	22,3
	Postgraduate degree	60	22,0
	Master's degree	60	22,0
	Doctorate	6	2,2
Income	< R5 000	7	2,6
	R5 000 to R14 999	13	4,8
	R15 000 to R39 999	73	26,7
	R40 000 to R59 999	51	18,7
	R60 000 to R79 999	38	13,9
	R80 000 to R99 999	30	11,0
	>= R100 000	59	21,6
	Prefer not to say	2	0,7

Source: Author's own compilation

The sample of bank employees who use banking applications who participated in this study was dominated by females making up 63.7% (n = 174) of the 273 sample. Males made up 35.5% (n=97), and 2 (0.7%) participants did not disclose their gender.

The study respondents were racially diverse with 47.6% (n = 130) being black, 29.7% (n = 81) white, 12.1% (n = 33) Indian and 7.7% (n = 21) coloured. 2.9% (n = 8) did not indicate their racial identity.

The age distribution showed that most of the participants were over the age of 35 with the largest group between 36 and 45 years old (n =113; 41.4%). The second largest group was between 46 and 55 years old (n = 78; 28.6%) followed by 26 to 35 (n = 58; 19.8%). 7% of the respondents were aged between 56 and 65. The smallest age group was between the ages of 20 and 25, totalling nine participants.

The sample participants were highly educated, with 7.3% (n = 20) indicating matric was their highest level of education. Almost 50% of the sample had postgraduate qualifications with 22% (n = 60) having a postgraduate diploma, 22% (n = 60) with a master's degree and 2.2% (n = 6) with a doctorate.

The largest income group in the sample was between R15 000 and R 39 000 at 26.7% (n = 73) followed by R40 000 to R59 000 at 18.1% (n = 51). The groups earning between R60 000 and R79 999 and R80 000 and R99 999 made up 13.9% (n = 38) and 11% (n = 30) respectively of the total sample achieved. It was noted that 21.6% (n = 59) of the sample claimed to earn over R100 000 per month. 4.8% (n = 13) of the participants earned between R5 000 and R15 000 and the smallest income group earned below R5000 with 7 (2.6%) participants.

Table 4.1.2 shows banking applications mostly used by respondents. The distribution of banking applications used was heavily skewed to Nedbank with 50.9% (n = 139). FNB (RMB) was used by 18.7% (n = 51) followed by ABSA at

9.5% (n = 26). 8.4% (n = 23) of the sample indicated Standard Bank was their main banking application followed by Capitec (5.9%; n = 16), with Investec and Discovery both at 2.2% (n = 6) and 3 (1.1%) participants stating Tymebank was their mostly used banking application. Three participants (1%) indicated that their primary banking application was not listed and selected “Other”.

Table 4.1.2 Banking application used

Characteristics		Frequency	Percent
Banking app used the most	Nedbank	139	50,9
	FNB (RMB)	51	18,7
	ABSA	26	9,5
	Standard Bank	23	8,4
	Capitec	16	5,9
	Discovery Bank	6	2,2
	Investec	6	2,2
	Tymebank	3	1,1
	Other	3	1,1

Source: Author’s own compilation

4.2 Central Tendency Measures of Variables and Measurement Items

This section expands on the measures of the central tendency of the unobserved constructs used in the study. These were INNO, FKN, FSE, SE, and SI which made up the exogenous variables. They were followed by PE, EE, SI, HM, ATT, TP, and IU which were the endogenous variables. Coll, UA, and IC were used as moderators of SI and TP. A five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree was used to assess respondents’ perceptions. Results of the means, standard deviations, skewness, and kurtosis of all indicators are presented followed by an explanation of each result.

4.2.1 *Innovativeness*

Innovativeness is a construct measuring the degree to which individuals believe they take up and adopt new ideas or technology in relation to others. It is measured by four constructs. Table 4.2.1 summarises the results from the descriptive analysis of personal innovativeness.

Table 4.2.1 Innovativeness

	Mean	Std. Deviation	Skewness	Kurtosis
INNO1	4,36	,905	-1,874	3,863
INNO2	3,77	1,151	-,806	-,182
INNO3	4,02	1,171	-1,282	,768
INNO4	3,97	1,044	-1,163	,972
Overall INNO	4,03	,885	-1,106	1,267

Source: Author's own compilation

The table shows the descriptive statistics of innovativeness using the four items identified in the literature. The overall mean score for innovativeness was 4.03 and a standard deviation of 0.885, indicating participants see themselves as innovative and tend to take a short time to adopt new ideas. Kurtosis was at 1.267 and skewness at -1.106 indicating the distribution was leptokurtic with a long-left tail.

4.2.2 *Financial Knowledge*

Financial knowledge measures how the study participants assess their basic financial knowledge using three indicators. The results are shown in Table 4.2.2.

Table 4.2.2 Financial Knowledge

	Mean	Std. Deviation	Skewness	Kurtosis
FKN1	4,19	1,144	-1,507	1,353
FKN2	4,37	,922	-1,939	4,004
FKN3	4,03	1,161	-1,257	,694
Overall FKN	4,10	,953	-1,380	1,638

Source: Author's own compilation

As shown in Table 4.2.2, the study respondents had an overall mean score of 4.1 for financial knowledge with a standard deviation of 0.953. This suggests that respondents in the study have a high level of self-reported financial knowledge with low levels of variation. Kurtosis of 1.638 shows the distribution was leptokurtic, and skewness of -1.38 indicates a longer left tail and more values on the higher end.

4.2.3 *Self-efficacy*

Self-efficacy measures banking application users' judgment of their capabilities to use PFM. This was measured with three items. Results from the study are shown in Table 4.2.3.

Table 4.2.3 Self-efficacy

	Mean	Std. Deviation	Skewness	Kurtosis
SE1	3,51	1,216	-,617	-,479
SE2	4,08	1,021	-1,137	,884
SE3	3,47	1,254	-,368	-,881
Overall SE	3,68	,796	-,465	,349

Source: Author's own compilation

The table shows that respondents had an overall score of 3.68 with a standard deviation of 0.79. This suggests that respondents in this study had a high level of self-efficacy. Kurtosis of 0.349 is close to a normal distribution but with a slightly sharper peak. The skewness of -0.465 indicates responses had a long left tail with more on the positive side of the mean.

4.2.4 *Financial Self-efficacy*

Financial self-efficacy measures respondents' belief in their capabilities to make financial management decisions. The study used three items to measure this construct, and the results are shown in Table 4.2.4.

Table 4.2.4 Financial self-efficacy

	Mean	Std. Deviation	Skewness	Kurtosis
FSE1	4,46	,757	-1,918	5,039
FSE2	4,42	,814	-1,892	4,450
FSE3	4,18	,963	-1,387	1,828
Overall FSE	4,35	,753	-1,712	4,079

Source: Author's own compilation

Respondents' overall financial self-efficacy score was 4.35 with a standard deviation of 0.753 suggesting that they have high levels of financial self-efficacy with low levels of variation. Kurtosis of 4.079 indicates the distribution is leptokurtic with response concentrated at the mean. A skewness of -1.712 shows that the distribution was negatively skewed.

4.2.5 *Social Influence*

Social influence is the extent to which users perceive their significant relationships and believe they should use PFM features in banking applications. The study measures this with three items and the results are shown in the table below.

Table 4.2.5 Social influence

	Mean	Std. Deviation	Skewness	Kurtosis
SI1	2,90	1,248	,021	-,802
SI2	3,00	1,241	-,109	-,851
SI3	2,75	1,207	,145	-,722
Overall SI	2,88	1,062	,046	-,382

Source: Author's own compilation

Table 4.2.5 shows that the overall social influence score from the study participants was 2.88 with a kurtosis of -0.382. This indicates that users of banking applications believe people significant to them do expect them to use PFM features in their banking applications, and the distribution is platykurtic with a flat peak. The standard deviation was 1.062, showing moderate variation in the responses. A skewness of 0.046 shows the distribution was positively skewed with fewer participants agreeing to the statements.

4.2.6 *Effort Expectancy*

These variables measure banking application users' expectations about the ease of using their banks' PFM tools using three indicators. Table 4.2.6 summarises the results from the descriptive analysis.

Table 4.2.6 Effort expectancy

	Mean	Std. Deviation	Skewness	Kurtosis
EE1	4,17	1,026	-1,393	1,618
EE2	3,99	1,020	-1,088	,943
EE3	4,07	,972	-1,126	1,119
Overall EE	4,08	,938	-1,243	1,515

Source: Author's own compilation

Ease expectancy was made up of three items identified in the literature. The overall EE mean of 4.08 and standard deviation of 0.938 indicate participants find PFM features in their banking applications easy to use. The individual item scores range from 3.99 to 4.17, indicating participants agreed with the statements on ease of use of PFM features. Responses were negatively skewed and had a kurtosis of 1.515, indicating a leptokurtic distribution.

4.2.7 *Performance Expectancy*

This unobserved construct uses three indicators to measure how banking application users expect PFM tools to perform. Table 4.2.7 summarises the results from the descriptive analysis of perceived usefulness.

Table 4.2.7 Perceived usefulness

	Mean	Std. Deviation	Skewness	Kurtosis
PE1	3,44	1,140	-,548	-,414
PE2	3,34	1,172	-,373	-,630
PE3	3,35	1,168	-,319	-,689
Overall PE	3,37	1,068	-,401	-,392

Source: Author's own compilation

Table 4.2.7 shows the descriptive statistics of PE (performance expectancy) using the three items identified in the literature. The overall PE mean of 3.37 and standard deviation of 1.068 indicate that participants have marginally above neutral levels of performance expectancy of PFM tools in their banking apps. The individual item scores range from 3.34 to 3.44, marginally over the neutral score of 3. The standard deviations ranged from 1.14 to 1.72, indicating a moderate level of diversity in the responses. The skewness of -0.401 shows the responses were slightly skewed to the left, with more responses above the neutral score of 3. Kurtosis of -0.392 indicates a platykurtic distribution.

4.2.8 *Hedonic Motivation*

Hedonic motivation is measured using three items. This construct measures how much users of banking applications enjoy using PFM features. Table 4.2.8 shows the results of descriptive statistics.

Table 4.2.8 Hedonic motivation

	Mean	Std. Deviation	Skewness	Kurtosis
HM1	3,50	1,054	-,479	-,181
HM2	3,56	1,042	-,427	-,245
HM3	3,61	1,029	-,505	-,160
Overall HM	3,55	,992	-,473	-,092

Source: Author's own compilation

The HM variable has a mean of 3.55 and a standard deviation of 0.992. This indicates that users feel a moderate level of enjoyment when using PFM tools in their banking applications. Mean scores of the items range from 3.50 to 3.61, and standard deviations of the indicators from 1.029 to 1.054 show a low level of diversity in the scores. Skewness of -0.473 and kurtosis of -0.092 indicate a left platykurtic distribution.

4.2.9 *Attitude*

In this study, attitude towards using PFM features is measured using three items. Attitude measures the positive or negative feelings toward using banking application PFM features. Table 4.2.9 shows the result from the study.

Table 4.2.9 Attitude towards PFM features

	Mean	Std. Deviation	Skewness	Kurtosis
ATT1	4,12	,984	-1,206	1,303
ATT2	3,96	1,025	-1,165	1,282
ATT3	3,98	1,019	-1,026	,826
Overall ATT	4,02	,909	-1,175	1,648

Source: Author's own compilation

Table 4.2.9 shows that the attitude indicator means ranged from 3.98 to 4.02, with kurtosis ranging from 0.826 to 1,303. The overall attitude score was 4.02, showing that banking users have a positive attitude towards PFM features in banking applications. Skewness for overall attitude was -1.175, indicating more positive scores than negative, with kurtosis at 1.648, suggesting a leptokurtic distribution characterised by a sharp peak with responses concentrated around the mean. The standard deviation of the overall attitude score was 0.909, indicating moderate diversity in these perceptions among respondents.

4.2.10 *Trust*

Trust measures the extent to which users believe the PFM features in their banking applications will perform as expected, helping them manage their finances. Three indicators were used to measure trust. Table 4.2.10 shows the results of the study.

Table 4.2.10 Trust in PFM features

	Mean	Std. Deviation	Skewness	Kurtosis
TP1	3,78	1,009	-,803	,499
TP2	3,62	1,040	-,548	-,113
TP3	3,45	1,122	-,362	-,585
Overall TP	3,62	,907	-,485	,213

Source: Author’s own compilation

Table 4.2.10 shows the overall trust score to be 3.63 with a standard deviation of 0.907, indicating that participants have a high level of trust in PFM features for banking applications, with moderate variation in the scores. A Kurtosis of 0.213 is close to a normal distribution, with slightly heavier tails. Skewness was -0.485, indicating a negative skew, with a greater number of respondents agreeing with the statements.

4.2.11 *Collectivism*

Collectivism is a cultural construct measuring the extent to which respondents value relationships with others and group success over individual achievement. This was measured with three items, and the results are displayed in Table 4.2.11.

Table 4.2.11 Collectivism

	Mean	Std. Deviation	Skewness	Kurtosis
COLL1	2,90	1,209	,138	-,974
COLL2	2,96	1,230	,036	-1,019
COLL3	3,31	1,258	-,270	-,980
Overall COLL	3,06	1,027	-,053	-,585

Source: Author's own compilation

Table 4.2.11 shows the overall collectivism score was 3.06 with a standard deviation of 1.027. This indicates that respondents in this study were slightly collectivist, with some variation in their levels. The overall kurtosis suggests the distribution was platykurtic. The skewness of -0.053 suggests that the distribution was close to being symmetric around the mean, with a slight tendency for values to be above 3.06.

4.2.12 *Uncertainty Avoidance*

Uncertainty avoidance is an unobserved variable measuring the extent to which people in the study cope with ambiguity and uncertainty. This was measured using three items. Results from the study are shown in Table 4.2.12.

Table 4.2.12 Uncertainty avoidance

	Mean	Std. Deviation	Skewness	Kurtosis
UA1	4,54	,742	-2,240	6,762
UA2	3,51	1,295	-,448	-,960
UA3	2,18	1,225	,893	-,186
Overall UA	3,41	,751	,194	-,497

Source: Author's own compilation

Table 4.2.12 shows that the overall uncertainty avoidance score was 3.41 with a standard deviation of 0.751. This suggests that respondents in this study exhibited some tolerance for uncertainty, characterised by low levels of variation. Indicators ranged from 4.54 to 2.1. The responses were positively skewed, indicating more were below the mean, and the distribution was platykurtic with a kurtosis of -0.497.

4.2.13 *Indulgence*

Indulgence measures the extent to which banking application users suppress or succumb to gratification. This was measured with three items. Results from the study are shown in Table 4.2.13.

Table 4.2.13 Indulgence

	Mean	Std. Deviation	Skewness	Kurtosis
IC1	2,68	1,414	,238	-1,310
IC2	3,44	1,130	-,412	-,540
IC3	3,18	1,184	-,216	-,789
Overall IC	3,10	,831	,271	-,127

Source: Author's own compilation

Table 4.2.13 shows the overall indulgence score was 3.10 with a standard deviation of 0.831. This indicates that respondents in this study had a moderate level of indulgence with low variation. Indicators ranged from 2.68 to 3.44. The overall skewness was positive, with a kurtosis of -0.127, suggesting a platykurtic distribution.

4.2.14 *Intention to use*

Intention to use is a construct that measures how much people plan to use technology in the future. The descriptive statistics from this study are shown in Table 4.2.14.

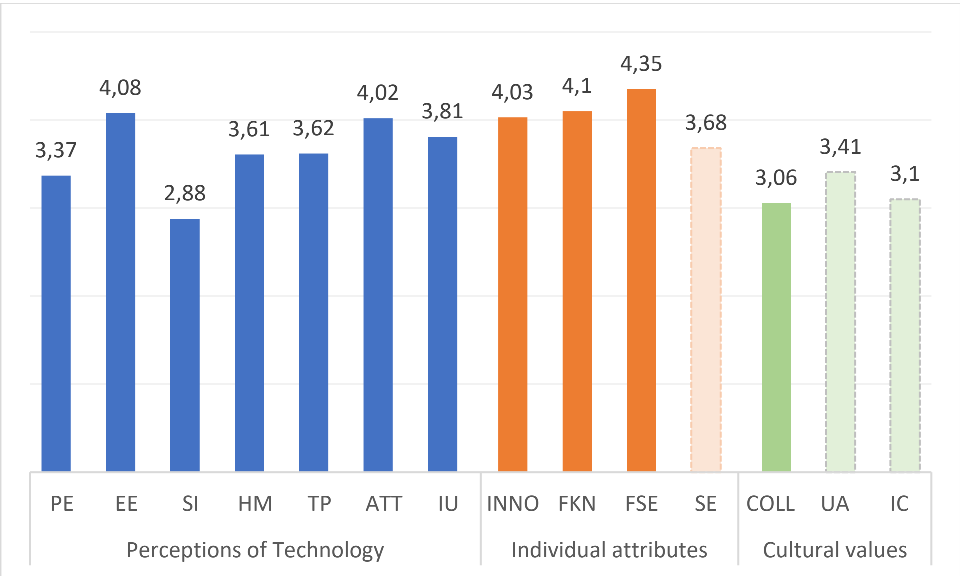
Table 4.2.14 Intention to use

	Mean	Std. Deviation	Skewness	Kurtosis
IU1	3,82	1,143	-0,974	0,207
IU2	3,80	1,144	-0,921	0,172
IU3	3,81	1,137	-0,922	0,110
Overall IU	3,81	1.087	-0,982	0,359

Source: Author's own compilation

The composite mean scores of all constructs are shown in Figure 3. The indicators for self-efficacy, uncertainty avoidance, and indulgent cultures were found to be unreliable. Therefore, they have been excluded and are represented in lightly shaded bars with dotted borders. All other constructs in the study passed reliability, validity, and discriminant validity tests, and the mean scores are displayed.

Figure 3: Composite mean scores



Source: Author's own compilation

Notes: lightly shaded bars indicate constructs that failed reliability tests

4.3 Structural Equation Modelling

This study uses covariance-based structural equation modelling (CB-SEM) to analyse the data following a two-step approach that consists of analysing a measurement model, followed by the structural model (Gerbing & Anderson, 1988). The analysis was conducted using IBM SPSS (Statistical Package of Social Science) and AMOS (Analysis of Moment Structures) version 29. The software is user-friendly and requires minimal programming to handle complex data analysis (Purwanto, 2021).

Before conducting the structural equation modelling, assumptions of normality and common method bias were verified. This was followed by validating variable item relationships and then the hypothesised relationships and paths through the structural equation model.

4.3.1 *Normality Testing*

Skewness and kurtosis were used to confirm normality in this study. The recommended values for skewness and kurtosis are between ±3 and ±10, respectively. Table 4.3.1 shows the results of the analysis, which confirms that all variables satisfy this condition.

Table 4.3.1 Normality test results

Variable	Skewness	Kurtosis
PE	-,401	-,392
EE	-1,243	1,515
HM	-,473	-,092
SI	,046	-,382
ATT	-1,175	1,648
TRUST	-,485	,213
IU	-,982	,359
COL	-,053	-,585
UA	,194	-,497
IC	,271	-,127
SEFF	-,465	,349
FEFF	-1,712	4,079
FKNOW	-1,380	1,638
INNO	-1,106	1,267

Source: Author's own compilation

Common bias method can arise when independent and dependent variables are measured using the same survey when using ordinal scales (Barry Babin, 2018).

4.3.2 *Correlation analysis*

The table below shows the Pearson correlation coefficients between all variables used in this study. The correlation between endogenous and exogenous variables being tested are highlighted in bold. The results are based on the composite constructs of each variable.

Innovation exhibits a strong positive correlation with the intention to use ($r = 0.399$, $p < 0.01$). Financial knowledge has a low correlation with intention to use ($r = 0.067$). Self-efficacy and effort expectancy have a moderate to strong correlation ($r = 0.399$, $p < 0.01$). Financial self-efficacy has a moderate correlation with effort expectancy ($r = 0.366$, $p < 0.01$) and a weak relationship with performance expectancy ($r = 0.182$, $p < 0.01$).

Social influence has moderate to strong correlations with trust in PFM ($r = 0.379$, $p < 0.01$), hedonic motivation ($r = 0.498$, $p < 0.01$), and intention to use PFM ($r = 0.524$, $p < 0.01$).

Effort expectancy is correlated with trust ($r =0.576$, $p < 0.01$), performance expectancy ($r =0.521$, $p < 0.01$), attitude and intention to use ($r =0.339$, $p < 0.01$). Attitude had the strongest correlation with intention to use ($r =0.709$, $p < 0.01$). It also showed a strong correlation with hedonic motivation ($r = 0.627$, $p < 0.01$) and performance expectancy ($r = 0.498$, $p < 0.01$). Performance expectancy was correlated with trust ($r = 0.602$, $p < 0.01$) and intention to use ($r = 0.594$, $p < 0.01$). Hedonic motivation had a strong correlation with trust ($r = 0.543$, $p < 0.01$), and trust was strongly correlated with the intention to use ($r = 0.499$, $p < 0.01$).

The moderators between social influence and trust used in this study, namely collectivism ($r =0. 263$, $p < 0.01$), uncertainly avoidance ($r =0. 246$, $p < 0.01$) and indulgence ($r =0. 312$, $p < 0.01$) all had mild to moderate correlation with social influence. Each of the cultural constructs also had lower correlation with trust in PFM. Collectivism and trust was mildly correlated ($r =0.203$, $p < 0.01$). Uncertainty avoidance had weak correlation ($r =0.141$, $p < 0.01$). Indulgence had mild correlation with trust in PFM ($r =0. 229$, $p < 0.01$).

These findings provide the first view of relationships between variables that will be used to build a structured equation model to assess the drivers of intention to use PFM features in banking applications.

Table 4.3.2 Pearson correlation matrix

	Coll	IND	UA	Inno	FKN	SE	FSE	SI	EE	ATT	PE	HM	TP	IU
Coll	1													
IND	,361**	1												
UA	,248**	,364**	1											
Inno	,214**	,137*	,122*	1										
FKN	,162**	0,101	0,030	,351**	1									
SE	,133*	,193**	,176**	,346**	,120*	1								
FSE	0,085	0,024	,164**	,323**	,501**	,183**	1							
SI	,263**	,246**	,312**	,251**	0,033	,531**	0,115	1						
EE	0,071	0,042	0,060	,415**	,283**	**,339****	**,366****	,283**	1					
ATT	,173**	0,103	,193**	,429**	,203**	,580**	,329**	,476**	**,489****	1				
PE	,130*	,214**	,161**	,305**	0,074	,443**	**,182****	,426**	**,521****	**,560****	1			
HM	,221**	,183**	,226**	,375**	,143*	,437**	,260**	**,498****	,381**	**,627****	,463**	1		
TP	,203**	,141*	,229**	,376**	,164**	,380**	,307**	**,379****	**,576****	,593**	**,602****	**,543****	1	
IU	,189**	,236**	,258**	**,399****	**0,067**	,545**	,137*	**,524****	**,339****	**,709****	**,594****	,569**	**,499****	1

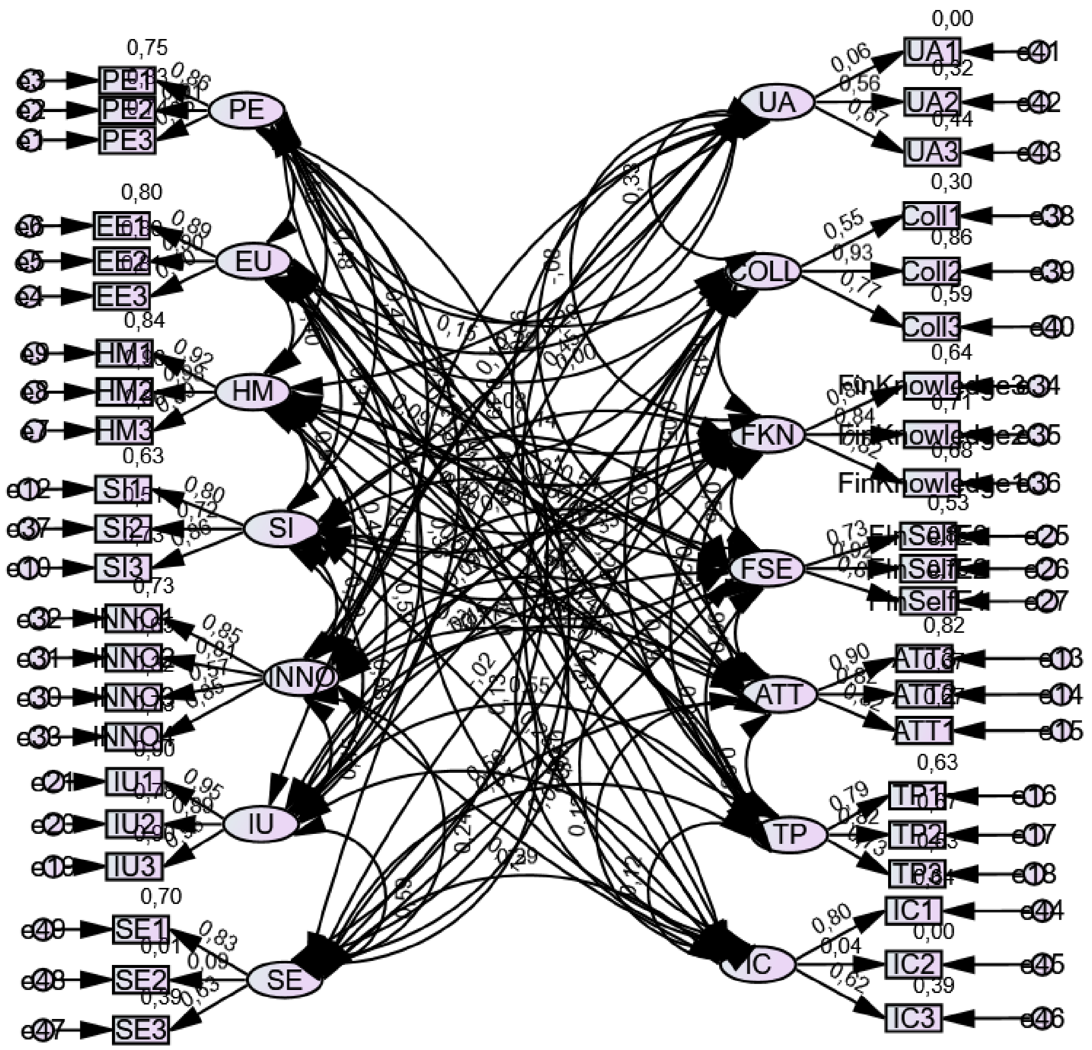
Source: Author's own compilation

*Note: ** indicates p-values < 0.01, * indicates p-values < 0.05*

4.3.3 *Measurement model: Confirmatory factor analysis*

Confirmatory factor analysis was used to assess the reliability and validity of the survey instrument (Hair & Sarstedt, 2019). This was used to assess how well-observed variables reflect the latent variables identified in theory. The measurement model of the survey instrument is depicted in Figure 4.

Figure 4: Measurement model



Source: Author's own compilation

The measurement model results were assessed for fitness using scientifically accepted indices, including root mean square error of approximation (RMSEA), comparative fit index (CFI), and the Tucker-Lewis index (TLI). Acceptable values for these indices are 0.05 or less for RMSEA, 0.95 or above for CFI, and 0.90 or higher for TLI (Xia & Yang, 2018). Chi-square and the ratio of chi-square to degrees of freedom (CMIN/DF) were also used to assess the model with a ratio less than three (3) indicating a well-fitting model as proposed by authors (Hair Jr et al., 2021). Table 4.3.3 summarises results for the acceptable levels for model fit.

Table 4.3.3 Acceptable measurement model fitness values

Fit indices	Acceptable values	Fitness
CMIN	< 3	Good
CMIN/DF	< 5	Sometimes permissible
RMSEA	<0.05	Good
	0.05 to 0.10	Moderate
	>0.5	Bad
PCLOSE	>0.00	Good
CFI	>0.95	Great
	0.90	Traditional
	0.80	Sometimes permissible
TLI	>0.9	Good
GFI	>0.80	Good
	>0.95	Great
AGFI	>0.8	Good

Source: Adapted from Hair et al. (2021) and Xia and Yang (2018)

The model fit test results are shown in Table 4.3.4. The validity and reliability of the model could be checked. Figure 4 shows the graphical representation of the measurement model from SPSS AMOS v29.

Table 4.3.4 Measurement model fit indices achieved

Fit indices	Value
CMIN	1336.919
CMIN/DF	1.739
RMSEA	0.52
PCLOSE	0.226
CFI	0.926
TLI	0.913
GFI	0.823
AGFI	0.782

Source: Author’s compilation

Reliability Analysis

Reliability assesses the internal consistency of indicators used to measure unobserved variables. Cronbach's alpha of 0.7 or higher is acceptable (Saunders & Lewis, 2012). The results of the reliability tests are shown in Table 4.3.5.

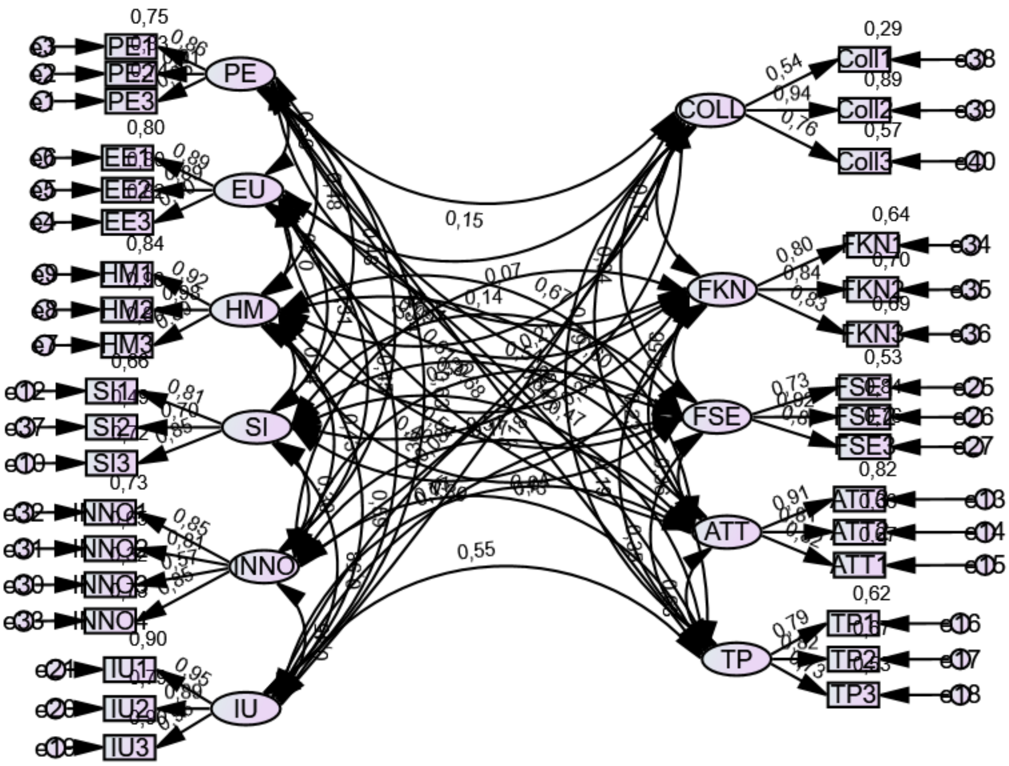
Table 4.3.5 Reliability analysis

Variable	Number of items	Cronbach's alpha
PE	3	0.910
EE	3	0.925
HM	3	0.949
SI	3	0.827
ATT	3	0.883
TRUST	3	0.819
IU	3	0.949
COL	3	0.780
UA	3	0.399
IC	3	0.371
SE	3	0.424
FEFF	3	0.865
FKNOW	3	0.856
INNO	4	0.843

Source: Author's compilation

All variables except UA, IC, and SE had acceptable values above 0.7. UA, IC, and SE have Cronbach alpha values of 0.399, 3.71 and 0.424, respectively. This suggests that the items do not accurately measure the unobserved construct and, as such, are not reliable. Because these variables failed the reliability test, they were excluded from the model. Figure 5 is a graphical representation of the updated measurement model.

Figure 5: Updated measurement model



Source: Author's own compilation

Model fit results from the updated measurement model are shown in Table 4.3.6 with improved indices all within the acceptable range.

Table 4.3.6 Updated measurement model indices achieved

Fit indices	Value
CMIN	739.692
CMIN/DF	1.567
RMSEA	0.46
PCLOSE	0.872
CFI	0.961
TLI	0.954
GFI	0.871
AGFI	0.837

Source: Author's compilation

Convergent Validity

The data was tested for convergent validity, which measures how well variables capture the various indicators (Barry Babin, 2018). Average variance extracted (AVE) has been used to test convergent validity by researchers (Fornell & Larcker, 1981). Fornell and Larcker (1981) introduced convergent validity to describe latent variables that explain over 50% of the observed variance. Recent studies also suggest minimum AVE values of 0.5 being acceptable for testing convergent validity, as indicators explain at least half of the variance observed (Barry Babin, 2018). Table 4.3.7 shows the AVE values of all the constructs for this study.

Table 4.3.7 Convergent validity results

Variable	Indicators	AVE
PE	3	0,775
EE	3	0,804
HM	3	0,866
SI	3	0,625
ATT	3	0,719
TP	3	0,609
UI	3	0,863
FSE	3	0,711
INNO	4	0,608
FKN	3	0,676
COLL	3	0,584

Source: Author's compilation

The table shows that all constructs have AVE values above the 0.5 threshold, suggesting satisfactory convergent validity. Collectivism (Coll) has the lowest AVE value of 0.58, indicating moderate convergent validity. However, it was above the threshold of 0.5, suggesting that the indicators explain more than half of the variance. The AVE values of all other constructs were above 0.6, with hedonic motivation (HM) being the highest at 0.866. This suggests it had the strongest convergent validity of all constructs in this study.

Discriminant Validity

Discriminant validity testing was conducted to determine the distinctiveness of each variable in the study. A technique used to test discriminant validity is to compare AVE with squared correlations (Fornell & Larcker, 1981). Fornell and Larcker (1981) suggested that the AVE for each variable must be greater than the squared correlations between variables. This suggests that each variable captures more internal variance within the construct than with the other variables, meaning each is distinct from the others. Table 4.3.8 shows the results from the analysis.

Table 4.3.8 Discriminant validity results

	PE	EE	HM	SI	ATT	TP	UI	FSE	INNO	FKN	COLL
PE	**0,880**										
EE	0,564	**0,897**									
HM	0,478	0,397	**0,930**								
SI	0,478	0,315	0,544	**0,791**							
ATT	0,610	0,541	0,666	0,539	**0,848**						
TP	0,685	0,645	0,600	0,466	0,683	**0,781**					
UI	0,629	0,364	0,587	0,582	0,773	0,551	**0,929**				
FSE	0,213	0,400	0,295	0,137	0,364	0,354	0,154	**0,843**			
INNO	0,342	0,451	0,434	0,296	0,508	0,432	0,445	0,329	**0,780**		
FKN	0,089	0,319	0,170	0,040	0,234	0,193	0,085	0,556	0,426	**0,822**	
COLL	0,148	0,073	0,205	0,329	0,192	0,262	0,180	0,043	0,224	0,169	**0,764**

Source: Author's compilation

The results confirm discriminant validity using the Fornell-Larcker criterion, showing that all square root values of AVE are higher than the correlations of the variable with all other variables. The diagonal variables in bold show the square root values of AVE. Each of these values is higher than all values in the corresponding rows and columns. As such, the discriminant validity of all variables being used in the study was established.

4.3.4 *Structural Model Analysis*

The measurement model passed the model fitness as shown in Table 4.3.6. Reliability, convergent validity, and discriminant validity were all established as shown in Table 4.3.7 and Table 4.3.8, respectively. The next step was to test the hypotheses in the structural model. The maximum likelihood estimation method was used to conduct the structural model analysis. The model tested is represented graphically in Figure 5. The results of the hypothesis testing are shown in Table 4.3.9.

Table 4.3.9 Hypothesis tests

Hypotheses	Relationships	Path Estimate (β)	t-value.	p-value	Results
H1	ATT ---> IU	0,607	9,149	***	Supported
H2	PE ---> IU	0,297	4,166	***	Supported
H3	EE ---> IU	-0,184	-3,161	,002	No supported
H4	SI ---> IU	0,208	3,799	***	Supported
H5	HM ---> ATT	0,465	8,474	***	Supported
H6	PE ---> ATT	0,282	4,552	***	Supported
H7	EE ---> ATT	0,203	3,445	***	Supported
H8	TP ---> HM	0,455	6,722	***	Supported
H9	SI ---> HM	0,320	4,905	***	Supported
H10	SI ---> TP	0,496	6,966	***	Supported
H11	TP ---> IU	-0,049	-,581	,561	Not supported
H12	TP ---> PE	0,587	7,467	***	Supported
H13	TP ---> EE	0,592	9,101	***	Supported
H14	EE ---> PE	0,205	2,877	,004	Supported
H15	SE ---> EE	-	-	-	-
H16	FSE ---> EE	0,235	4,235	***	Supported
H17	FSE ---> PE	-0,054	-1,018	,309	Not supported
H18	FKN ---> IU	-0,072	-1,670	,095	Not supported
H19	INNO ---> IU	0,139	3,123	,002	Supported

Source: Author's compilation

*Note: *** indicates p-values < 0.01*

Hypothesis 1 (H_1): Innovativeness has a positive influence on the intended use of personal financial management tools in banking applications.

The analysis indicates that innovativeness has a weak positive but significant influence on the intention to use PFM tools in banking applications. An increase of one standard deviation in perceived innovativeness increases the intentions to use PFM tools in banking applications by 0.139 standard deviations, with a 0.2% chance that the relationship is random ($\beta = 0.139$, $p = 0.002$), thus supporting H_1.

> Hypothesis 2 (H_2): financial knowledge has a positive influence on the intention to use personal financial management tools in banking applications.

The analysis indicates that financial knowledge has a negative and insignificant influence on the intention to use PFM tools in banking applications ($\beta = -0.072$, $p = 0.095$). This suggests that there is a 9.5% chance that the relationship between financial knowledge and intention to use PFM features in banking applications happened by chance. As such, the result is not statistically significant; therefore, we must accept the null hypothesis. H_2 is rejected.

> Hypothesis 3 (H_3): Self-efficacy is positively related to effort expectancy PFM features in mobile banking apps.

This hypothesis was not tested because the construct failed the reliability test, with a Cronbach's alpha below 0.5. This suggests that the indicators used for the construct did not result in sufficient internal consistency.

> Hypothesis 4 (H_4): financial self-efficacy has a positive influence on the effort expectancy of personal financial management tools in banking applications.

The analysis indicates that financial self-efficacy has a weak to moderate influence on the effort expectancy of PFM tools in banking applications ($\beta = 0.235$, $p < 0.001$), supporting H_4. A one-standard-deviation increase in financial self-efficacy results in a 0.235 increase in effort expectancy, with less than a 0.1% chance that this is due to chance. As such, the null hypothesis was rejected.

Hypothesis 5 (H_5): financial self-efficacy has a positive influence on the performance expectancy of personal financial management tools in banking applications.

The analysis indicates that financial self-efficacy has an insignificant negative influence on attitude towards PFM tools in banking applications ($\beta = -0.054$, $p = 0.782$), therefore rejecting H_5. There is a 78.2% chance that the negative impact on performance expectancy occurred randomly, and as such, the result is not statistically significant and supports the null hypothesis.

Hypothesis 6 (H_6): Social influence has a positive influence on the intention to use personal financial management tools in banking applications.

The analysis indicates that social influence has a positive impact on the intention to use PFM tools in banking applications ($\beta = 0.208$, $p < 0.001$). The analysis suggests that a 1-standard-deviation increase in social influence results in a 0.208 increase in intention to use PFM tools in banking applications. There is less than a 0.1% chance that this result was random, thus supporting H_6.

Hypothesis 7 (H_7): Social influence has a positive influence on trust in personal financial management tools in banking applications.

The analysis indicates that social influence has a moderate and significant positive influence on the trust of PFM tools in banking applications ($\beta = 0.496$, $p < 0.001$). A one-standard-deviation increase in social influence yields a 0.496-point lift in trust in PFM tools, thus supporting H_7 and rejecting the null hypothesis.

Hypothesis 8 (H_8): Social influence has a positive influence on hedonic motivation of personal financial management tools in banking applications.

The analysis indicates that social influence has a moderate positive and significant impact on the hedonic motivation of PFM tools in banking applications ($\beta = 0.320$, $p < 0.001$), thus supporting H_8. Hedonic motivation increases by 0.32 standard deviations with every one standard deviation increase in social influence. The null hypothesis is rejected as there is less than 0.1% chance of this occurrence being random.

> Hypothesis 9 (H_9): Trust in PFM features has a positive influence on hedonic motivation of personal financial management tools in banking applications.

The analysis indicates that trust has a moderate and significant positive impact on hedonic motivation regarding PFM tools in banking applications ($\beta = 0.455$, $p < 0.001$), thus supporting H_9. A one-standard-deviation increase in trust lifts hedonic motivation by 0.455 standard deviations. There is less than a 1% chance that the result is random, resulting in the rejection of the null hypothesis.

> Hypothesis 10 (H_{10}): Trust has a positive influence on intention to use personal financial management tools in banking applications.

The analysis indicates that trust has a negative but insignificant influence on the intended use of PFM tools in banking applications ($\beta = -0.049$, $p < 0.561$), thus rejecting H_{10}. The negative relationship between trust and intention to use has a 56.1% chance of being random, and, as such, we must accept the null hypothesis.

> Hypothesis 11 (H_{11}): Trust in PFM features has a positive influence on performance expectancy of personal financial management tools in banking applications.

The analysis indicates that trust has a strong, positive, and significant influence on the performance expectancy of PFM tools in banking applications ($\beta = 0.587$, $p < 0.001$), thus supporting H_{11}. A one-standard-deviation increase in trust of PFM features in banking applications results in a 0.587-standard-deviation increase in performance expectancy. The null hypothesis is rejected as the result is unlikely due to random variation.

Hypothesis 12 (H_{12}): Trust in PFM features has a positive influence on effort expectancy of personal financial management tools in banking applications.

The analysis indicates that trust has a strong and significant positive impact on the effort expectancy of PFM tools in banking applications ($\beta = 0.592$, $p < 0.001$), thus supporting H_{12}. An increase of one standard deviation in trust in PFM features yields a 0.592 standard deviation increase in effort expectancy, with a less than 0.1% chance that the result is due to chance. The null hypothesis was rejected.

Hypothesis 13 (H_{13}): Effort expectancy has a positive influence on the performance expectancy of personal financial management tools in banking applications.

The analysis reveals a weak but significant positive relationship between effort expectancy and performance expectancy of PFM tools in banking applications ($\beta = 0.205$, $p = 0.004$). An increase in effort expectancy by one standard deviation results in a 0.205 increase in performance expectancy with a 0.4% chance that the relationship is random. This result is statistically significant and rejects the null hypothesis, supporting H_{13}.

Hypothesis 14 (H_{14}): Performance expectancy has a positive influence on the intention to use personal financial management tools in banking applications.

The analysis indicates that performance expectancy has a weak to moderate positive impact on the intention to use PFM tools in banking applications ($\beta = 0.297$, $p < 0.001$), thus supporting H_{14}. A one-standard-deviation increase in performance expectancy increases intention to use by 0.297 standard deviations, with a probability of the result being random of less than 0.1%. This result is statistically significant, and the null hypothesis is rejected.

Hypothesis 15 (H_{15}): Effort expectancy has a positive influence on the intention to use personal financial management tools in banking applications.

The analysis indicates that performance expectancy has a weak, negative impact on intention to use PFM tools in banking applications (*$\beta = -0.184$*, *$p = 0.002$*), thus rejecting H_{15}. Each one-standard-deviation increase in effort expectancy results in a 0.184 decrease in intention to use, with a 0.2% chance that this is random.

Hypothesis 16 (H_{16}): Hedonic motivation has a positive influence on attitude towards personal financial management tools in banking applications.

The analysis indicates that hedonic motivation has a strong and positive influence on attitude towards PFM tools in banking applications (*$\beta = 0.465$*, *$p < 0.001$*), thus supporting H_{16}. Each increase of one standard deviation in hedonic motivation yields a 0.465 increase in attitude towards PFM features in banking applications. The chance that this result is random is below 0.1%, which is statistically significant; as such, the null hypothesis is rejected.

Hypothesis 17 (H_{17}): Performance expectancy has a positive influence on attitude towards personal financial management tools in banking applications.

The analysis indicates that performance expectancy has a weak to moderate impact on the attitude towards PFM tools in banking applications (*$\beta = 0.282$*, *$p < 0.001$*), thus supporting H_{17}. Attitude towards PFM features in banking applications increases by 0.282 standard deviations with every standard deviation increase in performance expectancy. The relationship has less than a 0.1% chance of being random and, as such, the null hypothesis is rejected.

Hypothesis 18 (H_{18}): Effort expectancy has a positive influence on attitude towards personal financial management tools in banking applications.

The analysis indicates that effort expectancy has minimal influence on attitude towards PFM tools in banking applications (*$\beta = 0.203$*, *$p = 0.003$*). Each increase of one standard deviation in effort expectancy increases attitude towards PFM features in banking applications by 0.203, with a 0.3% chance that the result is due to random variation. This is statistically significant and supports H_{18}.

> Hypothesis 19 (H_{19}): Attitude towards personal financial management tools in banking applications has a positive influence on intention to use personal financial management tools in banking applications.

The analysis indicates that attitude has a strong positive impact on the intention to use PFM tools in banking applications (*$\beta = 0.607$*, *$p < 0.001$*), supporting H_{19}. A one-standard-deviation increase in attitude towards PFM features in banking applications results in a 0.607-standard-deviation increase in intention to use. The results have less than a 0.1% chance of being due to random variation; as such, the null hypothesis is rejected.

4.3.5 *Moderation Analysis*

Moderators are constructs that impact the strength of relationships between variables (Hair Jr et al., 2021). This research aimed to explore the influence of cultural values on the use of PFM tools. Previous studies have found that individualistic cultural values have moderated the relationship between social influence and trust (Kurniasari et al., 2022). The moderating impact of collectivist culture was examined in relation to the influence of social factors on trust in PFM features in banking applications.

> Hypothesis 20 (H_{20}): Collectivism negatively moderates the relationship between social influence and trust in PFM features in banking applications.

Step 1: Mean centring

The variables of interest were SI, Coll, and TP. Composite variables were created for SI and Coll using the indicators. The variables were centred in SPSS by subtracting the mean from the composite value.

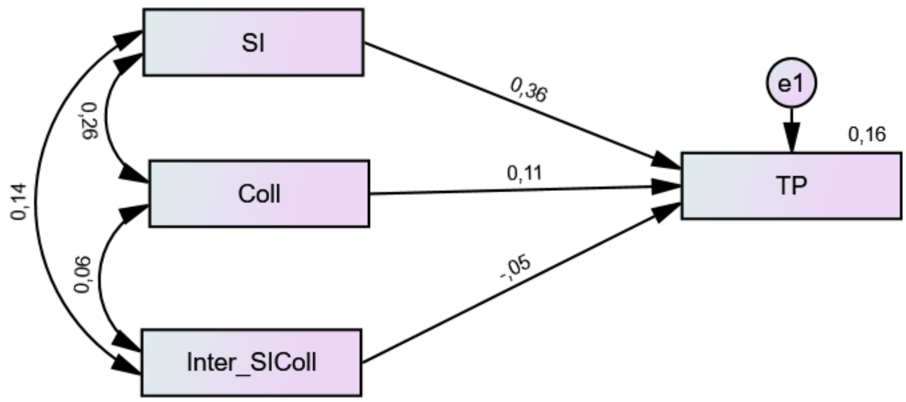
Step 2: Interaction term

An interaction term was created by multiplying the mean-centred values of the independent variable (SI) and the interaction term (Coll).

Step 3: Moderation model

AMOS v29 was used to draw the moderation model to test the relationship between SI, TP, and Coll. The model is represented in Figure 6: Moderation model (Trust)Figure 6.

Figure 6: Moderation model (Trust)



Source: Author's own compilation

The summary of the moderation effect of collectivist culture in the study is shown in Table 4.3.10.

Table 4.3.10 Moderation analysis results (Trust in PFM)

Relationships	Estimate (β)	t-value.	p-value	Results
SI ---> TP	0,357	6,144	***	
Coll ---> TP	0,112	1,933	,053	
Inter_SIColl ---> TP	0,052	-,927	,354	Not Supported

Source: Author's compilation

*Note: *** indicates p-values < 0.01*

The results of the analysis show that collectivism does not significantly moderate the relationship between social influence and trust of PFM features in banking applications (β = 0.043, t-value = -0.927, p-value = 0.354). As such, H_{20} was rejected. This suggests the levels of collectivism do not impact the relationship between social influence and trust of PFM features in banking applications.

Moderation analysis of uncertainty avoidance and indulgence versus restraint was not conducted because the constructs failed to meet the reliability tests.

CHAPTER 5. DISCUSSION OF RESULTS

This chapter builds on the results presented in the previous chapter by providing an interpretation of the findings. The chapter starts with a discussion of the demographics and central tendency measures. The hypotheses highlighted in the research are then interpreted to answer the research questions. The hypotheses' findings are triangulated with findings from previous studies.

5.1 Demographics

A total of 273 respondents who use banking applications were included in the study to answer the research questions. The sample was predominantly female (63.7%). All respondents below 21 and above 65 were excluded from the study, resulting in a sample consisting of adults aged between 26 and 55 (89.8%). Only 7% were aged 55 and above, and 3.3% were 25 and below.

Over 90% of respondents had post-matric qualifications. 7.3% of respondents indicated that matric was their highest level of education. The sample consisted of more people with post-matric qualifications, which does not accurately reflect national statistics, as it was predominantly comprised of financial sector employees who tend to be more educated and, therefore, are more likely to use banking applications. National statistics show that only 15.8% of South Africans aged over 20 have a post-matric qualification (Maluleke, 2024).

Over 90% earn more than R15,000, with 21.6% earning over R100,000, which is significantly higher than the national average. This is likely because the sample consists of employees from the financial sector.

The study showed that respondents use banking applications. The Nedbank app is used by 50.9% of the respondents, followed by FNB at 18.7%, ABSA at 9.5%, Standard Bank at 8.4%, and Capitec at 5.9%. The levels of banking app usage revealed by the study do not accurately reflect the South African banking market share, which is dominated by Capitec, with a market share of over 20%, and

Nedbank at 7% (BusinessTech, 2023). Nedbank dominated the sample because the respondents work for the bank and are more likely to use its applications. All the respondents in the sample were relevant to the study.

5.2 Discussion of Central Tendency Measures

Performance Expectancy

Respondents in the study also exhibited a moderate level of performance expectancy, with an overall mean score of 3.37 out of 5 and a moderate standard deviation of 1.068, indicating that they were slightly above the neutral point. This implies that the respondents' expectation that PFM features will help them manage their finances is relatively muted.

Effort Expectancy

The composite score for effort expectancy was 4.08 out of 5, indicating that participants found PFM features easy to use. This result could be influenced by the sample being bank employees who are familiar with technology.

Social Influence

Others' expectations highly influence people's view of technology (Roh et al., 2023; Yeh et al., 2023). The study participants exhibited a low level of social influence regarding the use of PFM features in banking applications, with a composite score below the neutral point (2.88). This could be a result of the technology still being relatively new to the market and having low levels of usage.

Hedonic Motivation

Many authors have identified the degree to which people enjoy using technology as a key factor in their adoption of it. The respondents exhibited moderate levels of hedonic motivation regarding PFM features in their banking applications, with a composite mean score of 3.61. This suggests a moderate level of enjoyment of these features. Similar findings have been reported in the use of mobile payments and NFC (Khalilzadeh et al., 2017).

Attitude

Despite having a slightly above-neutral performance expectancy, study participants had a positive attitude towards PFM features in banking applications. The mean score of 4.02 indicates that respondents generally agreed that using PFM features to manage their finances is a good idea.

Trust

Trust in technology refers to the degree to which users believe that it will fulfil its promises. Participants in the study had a moderate level of trust, with a composite mean score of 3.62. Many authors have identified trust as a key factor in the adoption of financial services technology.

Innovativeness

Personal financial management tools are a relatively new form of FinTech that has been introduced to users. As such, it was important to assess how receptive individuals are to using new technology. Study participants indicated that they perceived themselves as innovators based on a score of 4.03 out of 5 for the composite construct.

Financial Knowledge

Multiple authors have found that basic financial knowledge influences how people engage with FinTech. Respondents had a high level of self-assessed financial knowledge with a mean score of 4.1. This is not surprising, as the sample consisted of financial sector employees who are likely to be more financially literate.

Financial Self-efficacy

Financial self-efficacy is a construct used to assess an individual's perception of their ability to manage their finances effectively. This construct is important in wealth management FinTech. Due to the nature of the sample, the results for financial self-efficacy were very high at 4.35. Bank employees are more likely to have high levels of financial self-efficacy.

Collectivism

Study participants were predominantly neutral regarding their collectivism versus individualism. This suggests that there was not a strong slant towards either value in the sample.

Intention to Use

Results from the study suggest that participants have a high intention to use PFM features in their banking applications in future, with a composite score of 3.81.

5.3 Discussion of Hypothesis Testing Results

Discussion on research objective 1: Do users' individual attributes play a role in the adoption and use of the banking apps personal financial management features?

H1: Personal innovativeness has a positive effect on the intention to use PFM features in banking applications.

The results from the study support the hypothesis ($\beta = 0.150$, $p = 0.002$). Personal innovativeness has a weak but significant impact on the intention to use PFM features in banking applications. The adoption of mobile payment users in America was also found to have a positive impact on behavioural intention to use, at a 90% confidence level (Wu & Liu, 2023). Bouteraa et al. (2023) found that research on FinTech adoption revealed that perceived innovativeness significantly impacted adoption, aligning with the results of this study. Ashrafi (2023) found that innovativeness had a significantly stronger impact on the adoption of Robo-advisory services. This presents a potential barrier to adoption as usage might be limited to early adopters. PFM features are relatively new, and the results suggest that users who are more likely to try new technology first are also more likely to use their banks' PFM features.

H2: Financial knowledge has a positive effect on the intention to use PFM features in banking applications.

The results from the study reject the hypothesis ($\beta = -0.078$, $p = 0.092$). Financial knowledge was found to have a minimal, negative, and statistically insignificant impact on the intention to use PFM features in banking applications. This finding goes against other studies on the use of Robo-advisors (Yi et al., 2023). This suggests the levels of financial knowledge do not impact the use of PFM features in banking applications in the South African context.

H4: Financial self-efficacy has a positive effect on the intention to use PFM features in banking applications.

Findings from this study support the hypothesis ($\beta = 0.403$, $p < 0.001$). Financial self-efficacy has a strong, positive impact on effort expectancy. This is in line with findings on wealth management FinTech (Shiau et al., 2020)The results suggest that users who believe they can manage their finances will find PFM features easier to use.

H5: Financial self-efficacy has a positive effect on performance expectancy.

The analysis of the data revealed that financial self-efficacy did not have a significant impact on performance expectancy ($\beta = -0.018$, $p = 0.776$). This suggests that the level of user financial self-efficacy does not affect how useful they find PFM features in banking applications. This result was contrary to findings in the use of wealth management FinTech (Shiau et al., 2020).

These results suggest that, among the individual attributes examined in this research, financial self-efficacy and perceived innovativeness play a significant role in driving the use of PFM features in banking applications. Specifically, in making them easy to use with regards to financial self-efficacy and directly through perceived innovativeness.

Discussion on research objective 2: How do bank application users' perceptions of their bank's personal financial management features influence the adoption and use of these features?

H6: Social influence has a positive influence on the intention to use PFM features in banking applications.

Social influence was found to have a direct, positive effect on the intention to use PFM features in banking applications ($\beta = 0.224$, $p < 0.001$). Studies have yielded similar results when researching the adoption of digital payments in some regions (Wu & Liu, 2023). This suggests that users are more likely to use PFM features if people whose opinions they value recommend that they do so. This suggests that adoption can be improved by leveraging the social circles of bank application users. Social readiness was also found to be important in the context of NFC payments (Khalilzadeh et al., 2017).

H7: Social influence has a positive influence on trust in PFM features in banking applications.

Social influence had a strong, positive relationship with trust in PFM features in banking applications ($\beta = 0.463$, $p = <0.001$). These findings contradict previous findings concerning mobile payment adoption, which found no significant relationship. This suggests that users leverage the perceptions of others to trust PFM features in their banking applications. This could be due to people tending to rely more on others when it comes to receiving financial advice. Users of banking applications will be more likely to trust PFM features if people who influence them believe they should use them. This is because they rely on the fact that some people trust and recommend them.

H8: Social influence has a positive influence on the hedonic motivation of PFM features in banking applications.

The study's results show that the hypothesis was supported. Social influence had a strong, positive relationship with hedonic motivation ($\beta = 0.345$, $p < 0.001$). Findings regarding the use of NFC payments revealed a weaker relationship with hedonic motivation. However, the PFM feature tends to require more interaction. PFM features also enable users to compare their finances with others (Khalilzadeh et al., 2017). This could explain the stronger relationship between social influence and hedonic motivation. The results suggest that users ' enjoyment of PFM features is strongly influenced by others' expectations for them to use them.

H9: Trust has a positive impact on hedonic motivation towards using PFM features in banking applications.

Khalilzadeh et al. (2017) found that trust has a positive impact on hedonic motivation in the context of NFC payments. This result aligns with the findings of this research regarding PFM features in banking applications. The results could be due to the users' perception that using the tool will improve their financial well-being and, therefore, bring them enjoyment.

H10: Trust in PFM has a positive influence on intention to use PFM features in banking applications

This hypothesis was rejected in this study, implying that there is no relationship between trust and intention to use PFM ($\beta = -0.042$, $p = 0.463$). These findings contradict previous findings regarding mobile payment adoption, where no significant relationship was found. Studies show that trust influences the adoption and use of Robo-advisory financial technology (Yi et al., 2023). However, this study refers to features within banking applications. Banking application users have trust in their applications; therefore, trust in features within the application might not have a significant impact on their use.

H11: Trust in PFM has a positive influence on performance expectancy.

The research found that trust had a moderate impact on performance expectancy in PFM. This is in line with findings in digital payments (Khalilzadeh et al., 2017). Trust is a measure of how users perceive technology as meeting their expectations. This suggests that users who trust the PFM features are more likely to have higher performance expectancy.

H12: Trust in PFM features in banking apps is positively related to effort expectancy of PFM features in banking apps.

In line with previous studies in FinTech, this study also found that trust influences effort expectancy (Khalilzadeh et al., 2017). Trust is a component of expectation regarding the technology's ability to meet their needs. This implies that users with high trust in PFM tools expect that it will meet their effort expectations. This could be a result of the sample being comprised of banking staff who might have a more positive view of these tools than the average user.

H13: Effort expectancy has a positive influence on the performance expectancy of PFM features in banking applications.

The statistical analysis shows that the hypothesis was supported in line with findings from previous studies (Khalilzadeh et al., 2017). Effort expectancy has a strong positive relationship with effort expectancy ($\beta = 0.571$, $p = <0.001$). These results align with findings in digital payments adoption (Khalilzadeh et al., 2017). This implies that the easier PFM features are to use, the more useful banking applications users will find them to be.

H14: Performance expectancy has a positive influence on intention to use PFM features in banking applications.

Performance expectancy was found to have a strong relationship with the intention to use PFM features in banking applications ($\beta = 0.304$, $p < 0.001$). These findings align with the results of other studies on FinTech adoption across multiple regions (Wu & Liu, 2023). This suggests that users are more likely to utilise PFM features if they believe it will help them manage their finances more effectively.

H15: Effort expectancy has a positive influence on the intention to use PFM features in banking applications.

The study's results show that the hypothesis was supported. Effort expectancy has a moderate positive relationship with hedonic motivation ($\beta = 0.104$, $p = 0.044$). Similar findings were observed when looking at the use of NFC payments (Khalilzadeh et al., 2017). The results suggest that the easier the PFM applications are to use, the more enjoyable users will find them.

H16: Hedonic motivation has a positive influence on attitude toward PFM features in banking applications.

Results from the analysis show that hedonic motivation had the most substantial impact on attitude towards PFM features in banking applications among the constructs in the study ($\beta = 0.504$, $p = <0.001$); therefore, the hypothesis is supported. These results align with findings in FinTech and mobile banking adoption (Khalilzadeh et al., 2017; Saprikis et al., 2022). This suggests that making PFM features more enjoyable will have a strong impact on users' attitudes towards PFM features.

H17: Performance expectancy is positively related to users' attitudes towards PFM features in mobile banking apps.

The analysis suggests performance expectancy has a positive and significant effect on attitude towards PFM features in banking applications ($\beta = 0,231$, $p <0.001$); therefore, the hypothesis is supported. This suggests that users have a more positive feeling towards PFM if they have high expectations of how it will perform. This finding aligns with research on the use of NFC payments in restaurants and the adoption of Robo-advisors (Khalilzadeh et al., 2017; Roh et al., 2023). This study, therefore, confirms that the user performance expectation of their banking applications' PFM features will influence the attitude towards them.

H18: Effort expectancy has a positive influence on attitude towards PFM features in banking applications.

The analysis suggests a positive and significant relationship between effort expectancy and attitude towards PFM features in banking applications ($\beta = 0.224$, $p < 0.001$); therefore, the hypothesis is supported. This is in line with findings in payments and mobile banking (Khalilzadeh et al., 2017). Roh et al. (2023) also made similar findings regarding Robo-advisory FinTech. This suggests that perceptions of ease required to use PFM features in banking applications positively impact users' attitudes towards them.

H19: Attitude has a positive influence on intention to use PFM features in banking applications.

Attitude had the strongest impact on the intention to use PFM features in banking applications ($\beta = 0.606$, $p = <0.001$). These findings are in line with other studies on Robo-advisory adoption (Roh et al., 2023; Yeh et al., 2023). This suggests that users are more likely to utilise PFM features if they have a positive attitude towards them.

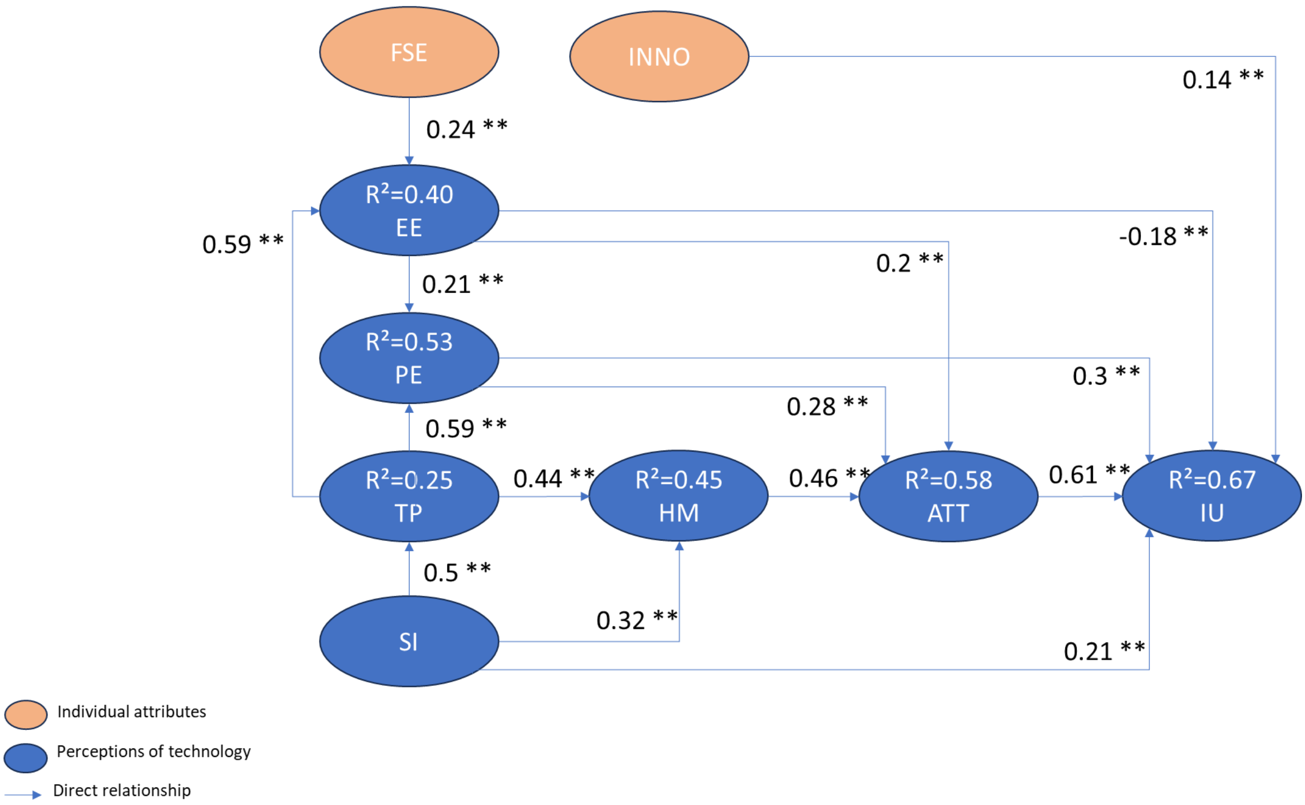
Discussion on research objective 3: Do individual cultural values influence the adoption of personal financial management features in banking apps?

This was tested by assessing the moderating impact of collectivism on the relationship between social influence and trust.

H20: Collectivism negatively moderates the relationship between social influence and trust in PFM.

The study's results fail to support the hypothesis of the moderation effect of collectivism. Individualism was found to moderate the relationship between social influence and trust in digital payments in Indonesia (Kurniasari et al., 2022). While this might seem disappointing, the implications are that cultural values are adequately accounted for by social influence. This aligns with findings that individualism did not have a moderating impact or made only a minimal contribution to the adoption of FinTech (Bommer et al., 2022; Picoto & Pinto, 2021).

Figure 7: Empirical structural model



Source: Author's own compilation

*Notes: ** = p value < 0.01*

Figure 7 illustrates the squared multiple correlations for the endogenous constructs in the model, represented as R^2, which ranges from 0 to 1. Trust for PFM has the lowest R^2 value, likely due to its proximity to the exogenous variable and the direct social influence that only impacts it. The model explains 40% of the variation in effort expectancy. Performance expectancy is influenced by trust and effort expectancy, with 53% of the variation in performance expectancy explained by this model. Social influence and trust both directly impact hedonic motivation, explaining 45% of the variation. Attitude is influenced by hedonic motivation, performance expectancy, and effort expectancy, and the model explains 58% of the variation. Ultimately, the model explains 67% of the variation of intention to use PFM features in banking applications.

CHAPTER 6. CONCLUSION

This chapter concludes the research by providing the practical implications of the study. It starts by reviewing the study's objectives. These findings are relevant to financial service providers seeking to arm their customers with better digitised financial management tools. The chapter also highlights some of the study's limitations and provides avenues for future research.

6.1 Study findings

The research aimed to address three key questions regarding the understanding of the drivers behind the intention to use personal financial management features in banking applications.

1. How do bank application users' perceptions of their bank's personal financial management features influence the adoption and use of these features?
2. How do banking application users' perceptions of themselves play a role in the adoption and use of the banking apps personal financial management features?
3. Do individual cultural values influence the usage of personal financial management features in banking apps?

The model developed for the study accounted for 67% of the variation in the intention to use PFM features in banking apps. Three individual attributes were assessed, namely innovativeness, financial knowledge, and financial self-efficacy. Financial knowledge was found to have a negative but insignificant impact on the intention to use PFM features. Innovativeness positively impacted the intention to use, implying that positioning must align with early adopters. Financial self-efficacy did not impact performance expectancy but had a significant positive impact on effort expectancy. This implies that financial institutions must build on their customers' financial self-efficacy to make their PFM features easier to use.

Users' perceptions of the technology were also assessed using constructs from UTAUT-TAM. These were performance expectancy, effort expectancy, social influence, hedonic motivations, trust, and attitude.

Attitude had the highest direct impact on the intention to use PFM features in banking applications, followed by performance expectancy, then social influence. This implies that financial institutions must find ways to improve their customers' positive feelings towards PFM features. Attitude is a central construct in many technology acceptance models (Khalilzadeh et al., 2017). Hedonic motivation, effort expectancy, and performance expectancy all have a significant impact on attitude. These constructs explain 58% of the variation of attitude.

The study found that hedonic motivation had the highest impact on attitude, followed by performance expectancy and then effort expectancy. This implies that making PFM features more enjoyable will have the most significant impact on attitude. Gamification and user experience enhancements have been found to improve hedonic motivation in digital banking. Hedonic motivations coupled with aesthetics have been found to increase engagement and perceived usability in online shopping (O'Brien, 2010). These could be leveraged to improve users' attitudes towards these features.

The model explained 45% of the variation in hedonic motivation. Trust and social influence were both found to impact hedonic motivation positively. This implies that finding ways to demonstrate how PFM features will help users meet their financial goals will enhance the enjoyment of these features. It also suggests that as more people who influence users' decisions believe they should use the features, they will enjoy them more.

Performance expectancy could be improved by giving users simple goals to achieve through targeted behaviour. The performance of the application would be assessed by how well it guides users to the targeted goal. Similar approaches have been employed in health and fitness applications, where users are provided with goals and the applications track and nudge them towards the target (Walsh & Lim, 2020).

While trust in PFM tools was found to be insignificant regarding directly driving intention to use the features in bank applications, it was found to play a central role in influencing other variables. These were performance expectancy, effort expectancy, and hedonic motivation. Trust has a strong impact on hedonic motivation. This implies that while trust might not directly drive intention to use PFM features, banks must still build on trust to improve performance expectancy, effort expectancy, and hedonic motivation.

Social influence had a strong positive impact on trust in PFM features. This implies that as more people who influence their decisions believe that they should use PFM features in their banking applications, they develop more trust in these features. Referrals and sharing of progress are commonly used on social media to drive electronic word of mouth (eWOM) (Reichelt et al., 2014). In e-commerce, eWOM has long been established as a driver of trust (Reichelt et al., 2014). Similarly, driving referrals could be used to improve trust and increase usage of PFM features in banking applications.

Individual attributes, namely financial self-efficacy and innovation, both contributed to the understanding of PFM usage. These provide avenues to improve usage by building on financial self-efficacy, particularly for individuals who are less likely to interact with new technology. The only cultural value assessed in this study was the distinction between collectivism and individualism. Collectivism did not moderate social influence and trust. This could be because social influence already accounts for the cultural values.

Of the original UTAUT constructs, performance expectancy was found to have a significant direct impact on the intention to use PFM features. Trust and effort expectancy were found to have a significant impact on performance expectancy. This suggests that as organisations build more trust in PFM and make it easier to use, performance expectancy improves.

6.2 Contributions

6.2.1 *Theoretical*

This study contributes to the existing literature on adoption and builds upon existing frameworks. The study explicitly adds individual attributes of financial self-efficacy and innovativeness to UTAUT-TAM to explain the intention to use PFM features in banking applications. The research adds to the existing body of knowledge by providing an African perspective on the adoption of PFM tools, as research on PFM usage has predominantly focused on America, Asia, and Europe (Nain & Rajan, 2024).

6.2.2 *Strategy*

This study offers insights that financial institutions can utilise to enhance the adoption and utilisation of PFM features. Trust in PFM tools is a key cornerstone that impacts performance expectancy, effort expectancy, and hedonic motivation, which are key antecedents for adoption. Financial organisations must optimise trust in their strategies to drive adoption.

Early adopters who perceive themselves as highly innovative could be targeted in the pilot and launch phases to build virality and drive social influence. Leveraging gamification and referral marketing are examples of how to increase social influence and hedonic motivation, which have been found to impact the attitude and usage of PFM tools directly. Ultimately, attitude has the most significant direct impact on intention to use PFM features in banking applications and must be a core focus for banks.

6.2.3 *Policy*

Regulators tasked with driving financial inclusion or achieving positive financial client outcomes can leverage these insights to assess the efficacy of PFM features developed by banks. The Financial Sector Conduct Authority (FSCA) is calling on the sector to improve financial education, as access to financial products is not sufficient for financial inclusion (Burger, 2024). PFM tools can be used to drive financial education. Understanding how in-person financial education can be leveraged to enhance financial self-efficacy and facilitate the use of PFM features in bank apps can improve financial inclusion.

Regulators must assess the synergies between in-person financial inclusion and the improved usage of PFM features in banking applications. This approach also caters for individuals with low levels of innovativeness. This would improve access to and usage of PFM tools, which have been found to drive better positive outcomes for users.

6.3 Limitations of the Study

The study had multiple limitations that must be noted. The first is that the data collection was based on a self-reported survey, which the respondents' biases could influence. Observation and experimentation may yield different results from the survey. Furthermore, the survey was quantitative and restricted the respondents’ ability to provide more depth and context that could help explain the results.

The study also had limitations in the types of PFM tools because it excluded users of non-bank applications. Understanding the use of PFM features provided by other types of financial institutions could give different results.

This study used financial service employees as the population. This limits the generalizability of the findings, as they may not apply to all users of banking applications. The working population outside of the financial sector may yield different responses than those obtained.

Only three cultural values were investigated from the six in Hofstede’s dimensions. The other constructs were found to impact the adoption of PFM features in banking applications significantly.

6.4 Suggestions for Further Research

This study investigated the factors that influence the adoption of PFM features in banking applications, including cultural values. Collectivism was the only cultural value from Hofstede’s six dimensions that was assessed in this research. Exploring the other dimensions might uncover strong relationships that impact the adoption of PFM features and applications.

Other factors that could drive adoption, such as the reputation of the banks, were not investigated and have been found to influence adoption in FinTech. Exploring the bank's reputation and how it influences adoption could reveal its impact on adoption.

The sample of respondents consisted of bank customers employed in the financial sector. Understanding how these factors drive adoption across other populations could yield results that expand the understanding of factors that drive the adoption of PFM features in banking applications.

Using different methods, such as experimentation, observation, and qualitative research, can provide various perspectives and greater depth into the factors that drive adoption, as well as uncover new barriers. This will enhance our understanding of the factors driving the adoption of PFM features in banking applications.

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Appendix

Figure 8: Moderation model (hedonic motivation)

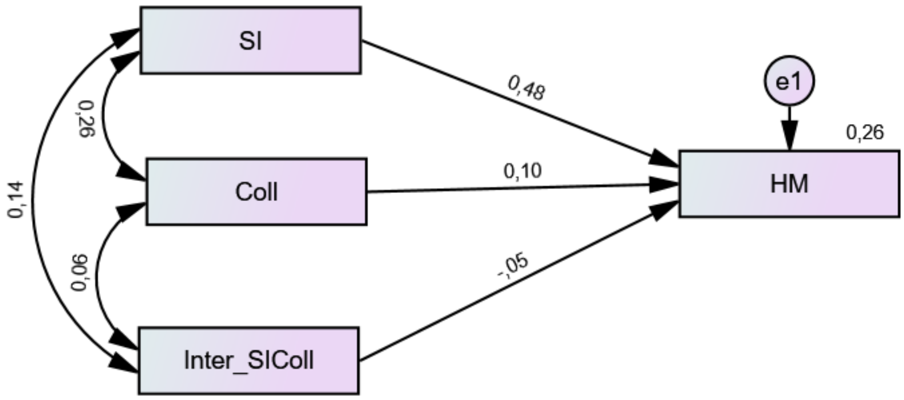


Table 6.4.1 Moderation analysis results (hedonic motivation)

Relationships	Estimate (β)	t-value.	p-value	Results
SI ---> HM	0,479	8,784	***	
Coll ---> HM	0,098	1,819	,069	
Inter_SIColl ---> HM	-0,052	-,981	,326	Not Supported

Figure 9: Moderation model (intention to use)

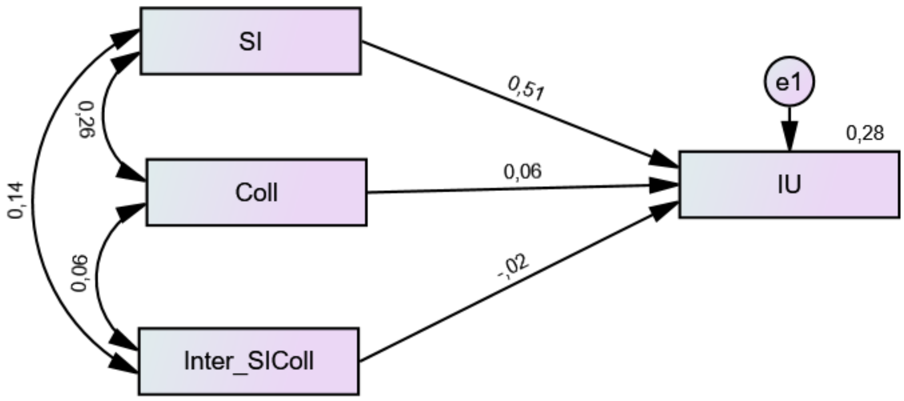
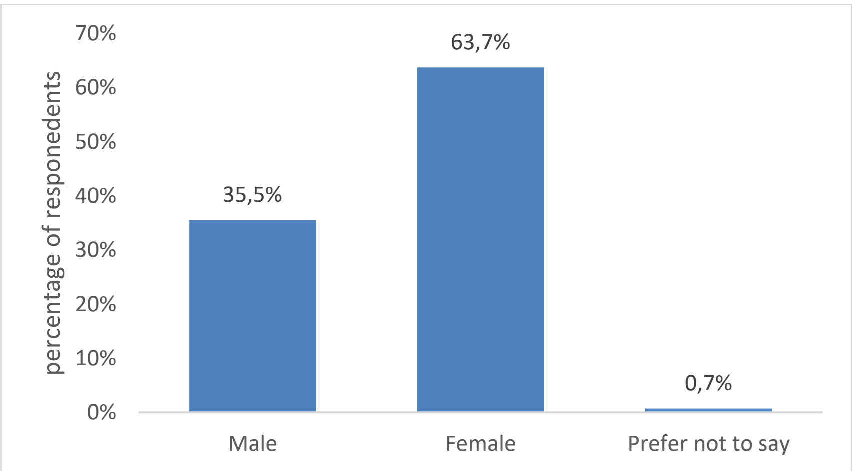


Table 6.4.2 Moderation analysis results (intention to use)

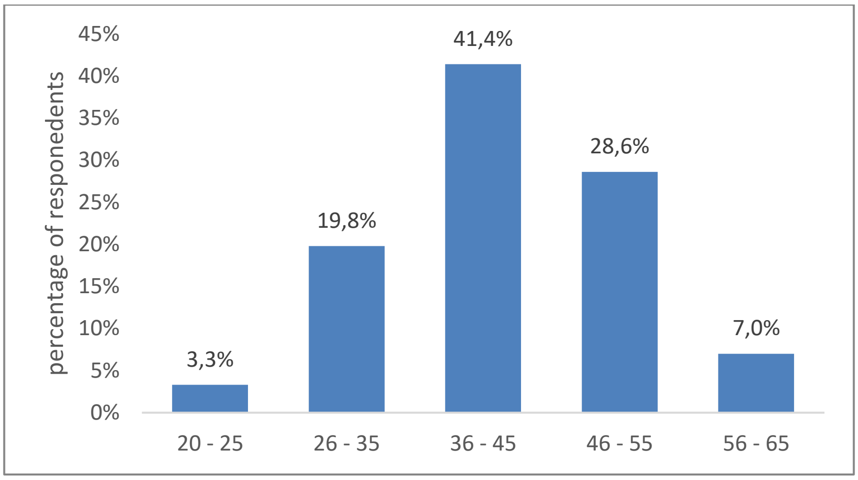
Relationships	Estimate (β)	t-value.	p-value	Results
SI ---> IU	0,512	9,501	***	
Coll ---> IU	0,055	1,034	,301	
Inter_SIColl ---> IU	-0,018	-,347	,729	Not Supported

Figure 10: Respondents' gender



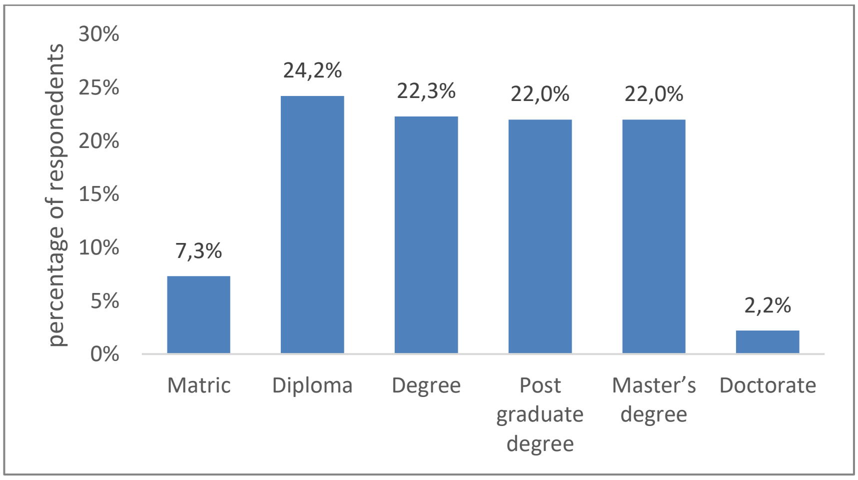
Source: Author's own compilation

Figure 11: Respondents' age



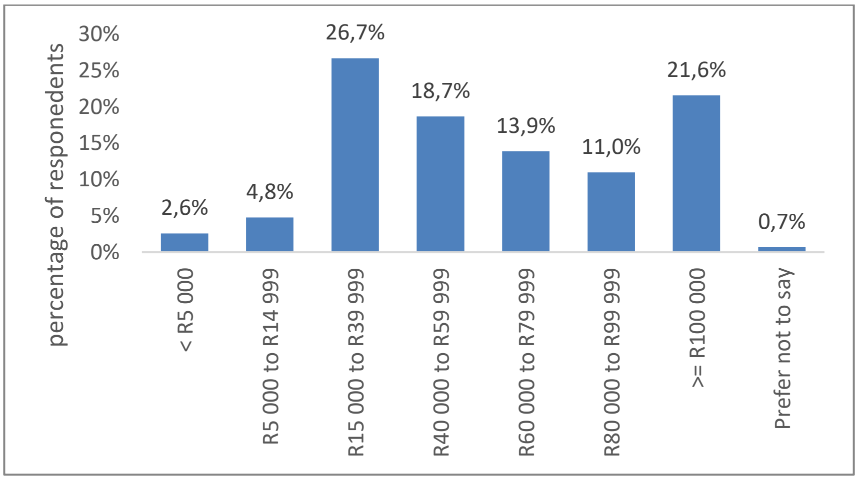
Source: Author's own compilation

Figure 12: Respondents' education



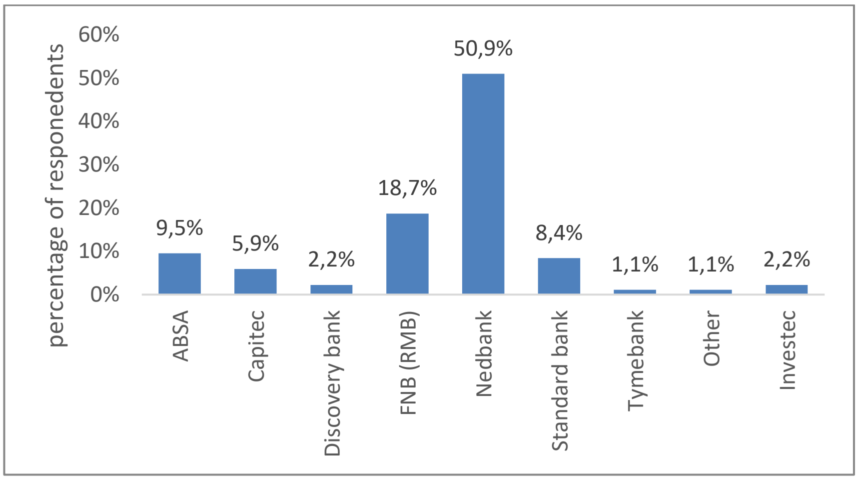
Source: Author's own compilation

Figure 13: Respondents income



Source: Author's own compilation

Figure 14: Main bank application used



Source: Author's own compilation