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AI Strategies for Financial Inclusion: A Multi-Analytical Approach to Mobile Financial Services Acceptance

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Declaration

I, Komlan GBONGLI, confirm that this dissertation submitted for my Ph.D. in Business and Organization Sciences with the finance subfield is my original work. Any uses made within it of the works of other authors in any form (e.g., ideas, equations, figures, text, tables) are appropriately acknowledged. A complete list of the references employed has been included.

Further, I have acknowledged all sources used and have cited these in the reference section.

Signed: Komlan GBONGLI

Miskolc, 2023

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Acknowledgments

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May all honor and glory be attributed to Almighty God.
Que tout honneur et toute gloire soient attribués au Dieu tout-puissant.

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ABSTRACT

Technological advancements, including artificial intelligence (AI), have emerged with considerable advantages in the recent commercial market, transforming the financial industry and facilitating financial inclusion. The widespread Internet-enabled phones, smartphones, and tablets associated with fast and reliable communications networks have encouraged banks and service providers to provide a new range of digital financial services that can be accessed through mobile phones. However, the success of technology remains not measured by how sophisticated it is but by how simply it merges with social life and derives its value from its usage on humanity.

Despite widespread access to Internet-enabled devices, the adoption of mobile financial services (MFS) remains surprisingly low, highlighting the need for a deeper understanding of mobile services acceptance.

Motivated by these challenges, this doctoral dissertation intends to understand the drivers of MFS better and, to some extent, mobile-based money services acceptance and use at the individual level to increase the adoption rate. To achieve these objectives, we developed five studies; three in the mobile financial services field and two regarding mobile money services. We started chapter two using a systematic literature review with weight analysis on the MFS sample of mainstream empirical published between 2011–2021 covering the COVID-19 pandemic period. Using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) format in chapter three, this framework-based review critically analyses the trend of technology acceptance model (TAM) –MFS-based studies of empirical research published from the last two decades in numerous scientific journals. In chapter four, the cross-sectional data from Togo were used to combine acceptance with trust and perceived risk at the multi-dimensional, simultaneously capturing success and resistance factors towards MFS adoption while prioritizing the major categories of this technology. In chapter five, the study develops a model to identify the direct and indirect effects and predict the drivers leading to the intention to adopt mobile money by extending self-efficacy, technology anxiety, and personal innovativeness with the technology acceptance model (TAM). In the sixth, as in the following study, we return to the multi-dimensional perceived risk factors in mobile money service to predict the resistance to adopting this technology during the COVID-19 pandemic.

Besides the weight analysis and the PRISMA framework-based, while providing a solid foundation and benchmark methodology for the studies, this dissertation includes structural equation modeling (SEM) in all the studies, explicitly relating it with (i) multiple criteria decision-making (MCDM) techniques in the fourth chapter, and (ii) an artificial neural network (ANN) in the fifth and sixth chapters.

Cconsidering the finding of all studies, the intention best drivers were (i) perceived risk, found significant in three studies, (ii) attitude, found significant in two studies with higher relative importance compared to personal innovativeness, (iii) subjective norms, perceived security, and trust were significant in two studies, and regarding the perceived risk best drivers were (i) perceived privacy risk, found significant in two studies with higher relative importance compared to time risk, monetary risk, and security risk. Regarding the studies individually, the dispositional trust and general trust effects on adopting MFS were found to be the most dominant drivers to explain the MFS use behavior, offering new direction on how the trust particular individuals' propensity

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to trust influences the usage behavior. Concerning the MFS classification, the study confirms the relevance of mobile money as the most chosen MFS category, followed by mobile payment and mobile banking, and recommends the inclusion of mobile money as a revolutionary tool for expanding access to financial services in low-resource environments. Personal innovativeness not only influences attitude but also has a direct and substantial relationship in predicting intention to use mobile money with a higher relative importance score, which indicates its importance in shaping attitude and intentions and furthers our understanding of the role of personality traits in innovation adoption. Perceived privacy risk as the most significant predictor of the overall perceived risk in mobile money is confirmed, showing that, to be mitigated efficiently, institutions can provide guidelines within privacy policies to support users in improving their security and privacy behaviors. Identifying individuals more likely to adopt MFS can be beneficial for marketing purposes, such as market segmentation and targeted marketing. The dissertation offers a framework on the most frequently used constructs in literature to comprehend how individuals behave towards accepting technology, categorized into three dimensions: Technological – Personal – Environmental (TPE) factors.

In summary, this work, driven by AI strategies, significantly contributes to both academic and practical fields by leveraging AI strategies to understand and predict MFS adoption. It introduces novel frameworks for categorizing MFS constructs, validate the effectiveness of SEM-ANN methodologies, and identify key predictors of adoption, including perceived usefulness, ease of use, and trust. These insights offer valuable guidance for financial stakeholders to enhance MFS adoption rates, tailor services, and expand financial inclusion efforts.

Keywords: Mobile, financial services, money, acceptance, TAM, SEM, MCDM, ANN, AI

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List of Abbreviations and Acronyms

AGFI	Adjusted Goodness-of-Fit Index
AHP	Analytic Hierarchy Process
AMOS	Analysis of Moment Structure
ANN	Artificial Neural Network
ASV	Average Shared Variance
AVE	Average Variance Extracted
CB-SEM	Covariance-Based Structural Equation Modeling
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
CI	Consistency Index
CLF	Common Latent Factor
CMB	Common Method Bias
CR (AHP)	Consistency Ratio
CR (SEM)	Composite Reliability
DTPB	Decomposed Theory of Planned Behavior
EFA	Exploratory Factor Analysis
E-TAM	Extended Technology Acceptance Model
FFBP	Feed-forward Back propagation
GFI	Goodness-of-Fit Index
GOF	Goodness of Fit Index
IS	Information System
KMO	Kaiser-Meyer-Olkin
MATLAB	Matrix Laboratory
MB	Mobile Banking
MCDM	Multiple Criteria Decision Making
MFS	Mobile Financial Services
MMS	Mobile Money Services
MMT	Mobile Money Transfer
MP	Mobile Payment
MSV	Maximum Shared Variance
NFI	Normed Fit Index
PLS-SEM	Partial Least Square Structural Equation Modeling
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
ReLU	Rectified Linear Unit
RMS or RMR	Root Mean Square Residual
RMSE	Root-Mean-Square-Error
RMSEA	Root Mean Square Error of Approximation
SEM	Structural Equation Modeling
SLR	Systematic Literature Review
TAM	Technology Acceptance Model
Tanh	Hyperbolic Tangent
TLI	Tucker-Lewis Index
TOPSIS	Technique for Order Preference by Similarity to an Ideal Solution
TPB	Theory of Planned Behavior
TRA	Theory of Reasoned Action
UTAUT	Unified Theory of Acceptance and Use of Technology
x^2	Chi Square
x^2/DF	Normed Chi-Square

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Chapter 1 Introduction

1.1 Research Background and Significance

Technological advancements, including artificial intelligence (AI), have revolutionized various sectors, notably the financial industry, by facilitating financial inclusion. The proliferation of Internet-enabled devices such as smartphones and tablets, coupled with fast and reliable communications networks, has driven banks and service providers to offer a wide array of digital financial services accessible through mobile phones. Despite these technological advancements, the true measure of success lies not in the sophistication of the technology but in its seamless integration into daily life and its ability to enhance human value.

Digital financial services (DFS), leveraging AI, are a crucial driver of economic growth (M. Kim et al., 2018). These services utilize digital technologies to promote financial inclusion by providing financial services to underserved populations. Mobile devices have become essential for consumers to access these services, including banking, payments, budgeting, and shopping. For many, especially the poorest populations, mobile phones are the first means of continuous communication and access to banking services. Mobile technology can make room for addressing two primary questions simultaneously: from the demand perspective, it represents an opportunity for financial inclusion among a population that is underserved by traditional banking services. From the supply side, it opens up the possibility for financial institutions to provide a great diversity of services at low cost to large customers of the poorest sections of society and people living in remote areas.

During the early 2000s, most mobile financial services providers could not meet market expectations due to their limited capability of handling data via mobile networks. As a result, the adoption rate of these services was lower than expected. To address this issue, mobile phone manufacturers introduced smartphones in 2006, which had enhanced web browsing and data transfer capabilities, better usability, enhanced information security, and a connected developer and mobile app ecosystem. The introduction of 3G, 4G, and 5G telecom network technologies, along with the transaction-making capabilities of internet banking, further improved the capabilities of smartphones, leading to increased demand for more advanced mobile financial services. Mobile financial services (MFS) is a broad term that includes various financial services that can be conducted on a mobile phone (Gbongli et al., 2020). It includes three leading forms: mobile banking, mobile payment, and mobile money transfer (Gbongli et al., 2020) (FIRPO, 2009). Mobile banking enables customers to interact with the bank through mobile phones, such as opening new accounts, obtaining account information, transferring funds, and making financial investments. Mobile payment allows users to make person-to-business payments for goods and services through mobile phones at the point of sale or remotely. Mobile money refers to the service allowing users to transfer money between people with less access to bank accounts (M. Kim et al., 2018) (Gbongli et al., 2019). Customers are gradually adopting these services as it increases their convenience by excluding the need for coins and cash for small transactions.

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According to a report by GSMA (2021), registered mobile money accounts reached 1.2 billion in 2020, with 5.2 million unique agent accounts globally and 310 mobile money deployments in 96 countries. The report also showed a 17 percent year-on-year increase in accounts and a 22 percent growth in total mobile money transaction values to $767 billion. With over $2 billion being processed daily and the industry doubling in value since 2017, the GSMA predicts that this value will exceed $3 billion daily by 2022, indicating significant growth opportunities in mobile money. However, the adoption rate remains low, highlighting the need for a deeper understanding of mobile services acceptance.

In Togo, despite the promising potential of mobile money services, the penetration rate is only 45%, compared to Ghana's 60% (Fiacre, 2018). This underscores the need to continually evaluate customers' readiness to adopt technology-based MFS that benefit both consumers and service providers. Two mobile telecommunication companies, Moov and Togocel, offer mobile money services in Togo, known as Flooz (launched in 2013) and T-Money (launched in 2016), respectively. The national social security fund (CNSS) has also encouraged employers to pay their social security contributions via these services (CNSS, 2019). However, data from BCEAO in 2018 shows that only 35% of the 3.9 million mobile money accounts in Togo are active, representing just 29% of the adult population. This indicates a partial understanding of the factors influencing MFS acceptance (Hassan Hosseini et al., 2015).

The slow adoption of mobile financial services can be attributed to several factors. Firstly, people have been hesitant to use mobile channels as they already have access to self-service channels like ATMs and Internet banking, as well as full-service channels like branches and call centers. The limited screen size of mobile phones has also hindered their usefulness (Ghose et al., 2013). The second reason is the perception of risk associated with using mobile financial services (MFS), particularly in developing countries like Togo, where privacy and security concerns are high (Gbongli et al., 2017). Customers may be uncertain or anxious about using MFS, leading further to slowing adoption (L. C. Hsu et al., 2019) (Gbongli, Peng, et al., 2016). This concern is not limited to developing countries; even in developed countries like Hungary, fraud risk in electronic payment transactions has been reported (Kovács & David, 2016). Despite these challenges, some emerging economies, such as the Philippines and Kenya, have successfully embraced MFS. According to recent research, in Kenya, M-Pesa, a mobile money service, has even been credited with lifting 2% of households out of poverty(Suri & Jack, 2016).

Various studies have examined the adoption of mobile financial services (MFS) using both qualitative and quantitative methods (Jadil et al., 2021) (Gbongli, 2022a). However, there has been a scant attempt to provide an integrative model that can explain the factors affecting MFS adoption comprehensively. The literature on MFS adoption is fragmented, which makes it challenging to build upon existing knowledge and advance research in the area. Given the complex nature of MFS as a combination of mobile and financial services, it is crucial to comprehensively understand the most significant drivers of mobile financial services (MFS) acceptance and use.

The following are the main motivational factors for undertaking this research:

1. While earlier studies have identified some drivers of MFS acceptance, adoption rates remain lower than expected. They have only been adopted by a few users (Deb & Agrawal, 2017) (Thakur & Srivastava, 2014) (Zhou, 2012a), revealing that novel constructs or relationships need to be discovered to advance knowledge in this area.

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2. Trust and risk might be critical determinants of MFS acceptance due to the inherent uncertainty of the mobile situation (H.-F. Lin, 2011). Given that risk perception may be higher than in traditional branch services (Koenig-Lewis et al., 2010), these constructs should be assessed together with adopting theoretical models.
3. Mobile money services are closely related to mobile banking and payment and are integrated parts of mobile financial services, which makes it sometimes hard to distinguish one from another.
4. Mobile money and mobile payment is a relatively novel field of study, under-explored compared to related research areas, including e-commerce or Internet banking, where studies have been extensively conducted and, therefore, must be investigated more.
5. Focusing on a single method to understand the potential drivers of MFS adoption may misrepresent the fundamental factors. Integrating multiple decision-making theories and predicting methodologies to assess the drivers of MFS digitalization for financial inclusion, particularly in developing countries, is essential. This practice can also seize a broader range of perspectives that a single technique might not capture
6. The MFS ecosystem in Togo lacks adequate customer empowerment for active participation and overcoming financial inclusion barriers. Therefore, Togo was chosen as an appropriate experimental field to assess and predict the key antecedents influencing users' behavioral intention to adopt MFS. Togo is an emerging economy located in sub-Saharan West Africa with a population of over 7.5 million people (UNdata, 2017). It shares borders with Burkina Faso to the north, Benin to the east, Ghana to the west, and the Gulf of Guinea to the south. In 2017, the country's economic growth rate was 4.5%, lower than the preceding year's growth rate of 5%. However, the economy made a substantial recovery in 2021, with a projected GDP growth rate of 4.8%, up from 1.8% in 2020. The recovery was primarily propelled by extractive industries and manufacturing on the supply side and private consumption and investment on the demand side (AfDB Group, 2022). According to the most recent report by the UN Development Program in 2022, Togo ranks 162 out of 191 countries on the Human Development Index (UNDP, 2022).

1.2 Technology Adoption Models and Theories

Studying the adoption of information technology contributes to assessing the acceptance rate, the drivers of acceptance, and the inhibitors factors users face in accepting this constantly evolving technology. The research on adopting new technology has led to advancing several concepts, theories, and models. Among these models that have been developed over the years, five theoretical currents prevail in the literature (Hoehle et al., 2012), including the innovation characteristics of the diffusion of innovations theory (DOI) (Rogers, 2003), the theory of reasoned action (TRA) (Hill et al., 1977), theory of planned behavior (TPB) (Icek Ajzen, 1991), technology acceptance model (TAM) (Davis, 1989), and theory of perceived Risk (TPR) (Featherman & Pavlou, 2003). In 2003 (Venkatesh et al., 2003a) compared the similarities and differences among the eight models earlier used in the information system area, all of which had their roots in sociology, psychology, and communications. These models are (i) TRA, (ii) TAM, (iii) TPB, (iv) Model of PC Utilization (Thompson et al., 1991a), (v)DOI, (vi) Motivational Model (MM) (Davis et al., 1992), (vii) Social Cognitive Theory (Compeau & Higgins, 1995), and (viii) an integrated model of technology acceptance and planned behavior.

TAM is probably one of the most widely cited models in technology acceptance (P. F. Wu, 2009). Since its advent, the TAM model has gradually drawn scholars' attention,

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being incrementally tested and applied to several technologies, from both individual and organizational use, within single or multiple countries. As TAM overlooked the social influence of adopting technology, it has some limitations in being applied beyond the workplace. Moreover, some variables as external constructs must be integrated into TAM to offer a more consistent prediction of system use (Taherdoost & Masrom, 2009) (Taherdoost et al., 2009). As the inherent motivations are not revealed in TAM, the application of TAM in a customer context where the acceptance and use of information technologies are not only to fulfill tasks but also to satisfy emotional needs may be restricted. TAM has been extended and adapted to the previous model version to the individual context referred to as ETAM to solve these issues. It has been proposed in two distinctive works. The first study emphasized perceived usefulness antecedents and BI (behavioral intention), regarded as TAM2. TAM2 was suggested by explicitly integrating two groups of constructs: social influence (image, subject norms, and voluntariness) and cognitive (result demonstrability, job relevance, and output quality) to TAM to enhance the predictive power of perceived usefulness. From this end, for both voluntary and mandatory environments, TAM2 outperformed. The only exception is associated with the subjective norm, which influences mandatory environments but does not in voluntary environments. The second study investigated constructs that impact perceived ease of use. The antecedents of perceived ease of use have been divided into adjustments and anchors. The general beliefs concerning the use of computer systems have been placed in anchors set (enjoyment and objective usability). In contrast, beliefs built on direct experience of a given system are incorporated in adjustments set (external control, computer self-efficacy, computer anxiety, and computer playfulness).

In this work, we apply TAM and other well-known constructs, including self-efficacy, technology anxiety, and personal innovativeness. Moreover, this study adopts a multidimensional trust and perceived risk model, as described in the following chapter.

1.3 COVID-19's Impact on Togo's Financial Market: A Socioeconomic Overview

COVID-19, the novel coronavirus, has significantly impacted the global economy, including Togo's financial market. The virus first emerged in Wuhan, China, in December 2019 and quickly spread worldwide, leading to widespread lockdowns and economic disruptions. The Togolese government also imposed measures to control the spread of the virus, which had a significant impact on the country's financial market. In this section, we will discuss the major effects of COVID-19 on the financial market in Togo and provide an overview of the current socioeconomic situation in Togo.

1.3.1 Effects of COVID-19 on the Financial Market in Togo

The COVID-19 pandemic has led to a significant slowdown in economic activity in Togo, directly impacting the financial market. The Togolese stock exchange, Bourse Régionale des Valeurs Mobilières (BRVM), has experienced a decline in trading activity due to the pandemic. Investors have been more cautious and risk-averse, which has led to a decline in investment activity. The pandemic also led to a decrease in foreign investment in Togo, further exacerbating the economic impact of the virus on the country. Furthermore, the pandemic has reduced consumer demand for products and services, resulting in decreased profits for businesses, consequently leading to a decrease in the market value of their stocks.

Another major impact of the pandemic on Togo's financial market was the decline in

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economic activity in the country. With many businesses forced to close due to the pandemic and the measures taken by the government to control its spread, the country's GDP growth rate slowed down. According to the 2020 World Bank report in Togo (Banque Mondiale, in the French language), a significant proportion of jobs have been impacted by the pandemic, with approximately 62% affected. The employment rate in the service sector has been most severely impacted, with a 49% reduction, while the industrial sector has experienced a decline of 13%. The report also highlights a 30% reduction in workers in retail and leisure industries and a 12% decrease in workplace attendance compared to pre-COVID-19 pandemic levels (Banque Mondiale, 2020). In their 2021 study, Dandonougbo et al. (2021) investigated the impact of COVID-19 on household food security and income variation in Togo. The study employs probit and multinomial logit models, utilizing data gathered from 1405 households across 44 districts within 6 health regions. The study's findings suggest that households whose heads have lost their jobs are more vulnerable to experiencing a decline in income and, subsequently, a decrease in their food intake.

The results indicate that cash transfers to vulnerable populations have a positive effect but are not statistically significant in influencing income changes. Moreover, the study also discovers that households that receive social benefits and whose heads possess higher levels of education are more likely to withstand the adverse impacts of the pandemic. Lastly, for households that have been moderately or severely affected by the crisis, the authors find a high probability of reducing their food consumption. Based on their results, they recommend extending social benefits to informal sector actors and accelerating the implementation of the single social register to target vulnerable households better. This decline in economic activity led to a decrease in government revenues and an increase in public debt, which strained the country's financial system.

The decline in economic activity has also affected the banking sector in Togo. The pandemic has led to increased loan defaults as many businesses have been unable to repay their loans due to reduced revenues. This has put pressure on the banking sector, which has been forced to increase provisions for loan losses. Furthermore, the pandemic has decreased deposits, as individuals and businesses have become more cautious with their money.

To counteract the economic impact of the pandemic, the Togolese government implemented a range of measures, including economic stimulus packages and monetary policy interventions. These measures aimed to support the financial sector, provide relief to businesses and households, stimulate economic growth, and encourage digital payments to reduce the use of cash, which could potentially reduce the spread of the virus. The government also worked to improve the country's healthcare system to control the spread of the virus and reduce the impact of the pandemic on the economy.

1.3.2 The Recent Togolese Socioeconomic Situation

Togo is a small West African country with about 8 million people. Over the past few years, the country has made some progress in improving its socioeconomic situation, although many challenges still need to be addressed.

The Togolese economy has been growing steadily over the past few years, with an average annual growth rate of approximately 5% (AfDB Group, 2022). One of the key drivers of Togo's economy is agriculture, which accounts for around 40% of GDP and employs most of the population. The government has implemented several policies to promote agricultural development, including establishing agricultural cooperatives and distributing fertilizers and other inputs to farmers. Togo has a significant industrial sector,

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with phosphate mining and cement production playing a significant economic role. In addition to agriculture, Togo has been developing its infrastructure, particularly its transportation networks. The country has invested heavily in building new roads and improving its ports, which has helped to facilitate trade and attract foreign investment.

Despite these positive developments, Togo still faces a number of challenges. Poverty remains a major issue, with around 55% of the population living below the poverty line. Unemployment is a significant problem, particularly among young people, with an estimated 30% of the country's youth unemployed (World Bank, 2021). Furthermore, Togo has struggled with political instability in recent years, which has affected its economic growth. The government has been criticized for lacking transparency and accountability, and widespread protests have called for political and economic reforms.

The COVID-19 pandemic has also had a significant impact on the Togolese economy. The pandemic has caused a decline in economic activity, reduced government revenues, and led to an increase in public spending on health and social welfare programs. The Togolese government has implemented various measures to mitigate the impact of the pandemic on the economy. These measures include tax relief, financial support to businesses, and increased health and social welfare program spending. The government has also encouraged digital payments to reduce the use of cash, which could potentially reduce the spread of the virus.

Regardless of the challenges posed by the pandemic, Togo has continued to implement various economic reforms to promote economic growth and development. The government has implemented reforms to improve the business environment, attract foreign investment, and promote regional integration. Togo is also a member of the West African Economic and Monetary Union (WAEMU), which has helped to promote regional economic integration and stability.

In conclusion, while Togo has made some progress in improving its socioeconomic situation, much work must be done to address the country's poverty and unemployment challenges and promote greater political stability and accountability. The COVID-19 pandemic has significantly impacted the Togolese economy, including the financial market. Its impact on the financial market in Togo leads to a decline in stock prices, a decrease in economic activity, and a strain on the country's financial system. The Togolese government has implemented various measures to mitigate the pandemic impact on the economy, but the long-term effects of the pandemic on the economy remain uncertain. Togo's economy has been growing steadily over the past few years, and the government has continued to implement economic reforms to promote economic growth and development.

1.4 Study Selection and Focus

The research literature on MFS (mobile banking, mobile payment, and mobile money) can be classified into three types of studies: (Donner & Tellez, 2008) (a) those that explain or predict the adoption of MFS; (b) those that assess the systems" impact on people and economies; and (c) a relative few that try to understand the use of such systems in social, economic, and cultural contexts. Alternates of this trichotomy, which distinguishes adoption studies from impact studies and from "use" studies, have been documented before (Orlikowski & Iacono, 2001) (Sein & Harindranath, 2004); this dissertation mainly selects the study on explaining and predicting the antecedents of MFS adoption in Togo, one of the developing countries.

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While most studies investigated MFS adoption in a single country (although the countries studied in the corresponding case are diverse), some studies compared it between developed and developing countries. Therefore, Frimpong et al. (2020) focused on a cross-national investigation of trait antecedents of mobile-banking adoption between the participants of the UK and Ghana (a neighboring country of Togo) through the survey data from 1,340 participants. The results indicated that intrinsic traits are more substantial in explaining consumers' attitudes toward mobile banking in Ghana than in the United Kingdom. However, no significant variance between the two countries was observed concerning the mediation effect of consumers' attitudes on the intention to use mobile banking. Moreover, a sample with 375 complete responses from US and Brazilian students revealed that trust and perceived ease of use are relevant factors to understanding mobile banking use in both countries (Malaquias & Hwang, 2019). Although economic and financial development is so closely linked, the results of the comparisons derived from developed and developing countries offer some information that the factors affecting mobile financial services are more influenced by the advancement of information technology, which has a significant impact on the creation of more flexible payment methods and user-friendly financial services.

Afawubo et al. (2020) investigated the socio-economic determinants of mobile money adoption and households' vulnerability to shocks in Togo. They found that mobile money increases households' ability to deal with some life emergencies, primarily environmental and agricultural vulnerabilities. When assessing whether better access to mobile networks is associated with increased mobile money adoption, Naito & Yamamoto (2022), using evidence from the micro-data of six Developing Countries, found that the overall mobile money adoption rate does not appear to affect how mobile networks impact on the use of mobile money. This suggests that the obstacle to using mobile money is not likely to come from the poor infrastructure but other reasons such as the reliability of mobile network providers, inconvenience, or culture.

Based on the viewpoints outlined above, this dissertation's core focus, as depicted in **Figure 1.1**, is to investigate and predict the main drivers of acceptance of mobile financial services (i.e., mobile banking, mobile payment, and mobile money) with a specific prominence on mobile money services for promoting financial inclusion in Togo. The work is only emphasized at the individual level of adoption; no firm or business level will be explored or studied. Interrelated IT acceptance fields and subjects, entailing Internet banking, mobile services, financial services, m-commerce, or mobile apps, are explicitly excluded from the study.

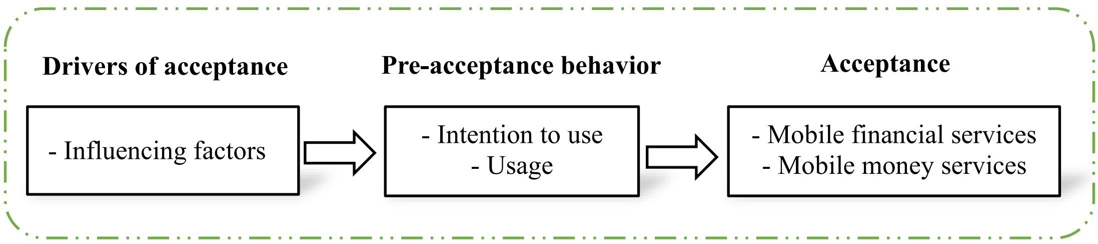

Figure 1-1 Research focus
Source: own elaboration

Mobile banking can be understood as a set of execution of financial services in the course of which, within an electronic procedure, the users apply mobile communication

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techniques involving the use of portable devices (Pousttchi & Schurig, 2004) or as a service whereby users utilize a mobile phone to access banking services and perform financial transactions (J. Anderson, 2010). Mobile payments are made or enabled via digital mobility technologies, from handheld devices, with or without mobile telecommunications networks. Ghezzi et al. (2010) recapitulate the notion of mobile payment as a process in which at least one phase of the transaction is conducted through a mobile device up to securely processing a financial transaction over a mobile network or via various wireless technologies. Mobile money services (MMS) use mobile phones to transfer money (Upadhyay & Jahanyan, 2016). Mobile money is run by mobile network operators (MNOs) and consists of transactions conducted through mobile phone networks to access customers' stored funds sustained by the MNOs. It uses nonbanking tools to extend financial services to subscribers that banks cannot reach (Malinga & Maiga, 2020).

To enhance our understanding of mobile banking, mobile payment, and mobile money acceptance, studying them in different contexts, samples, and groups is vital. If possible, use different theoretical frameworks and methodologies to ascertain relevant determinants that can add to the existing knowledge. For this purpose, our dissertation comprises five studies (as depicted in **Figure 1-2**), three focusing on mobile financial services and two on mobile money services. Additionally, our work represents the global distribution of mobile financial services through various systematic literature reviews.

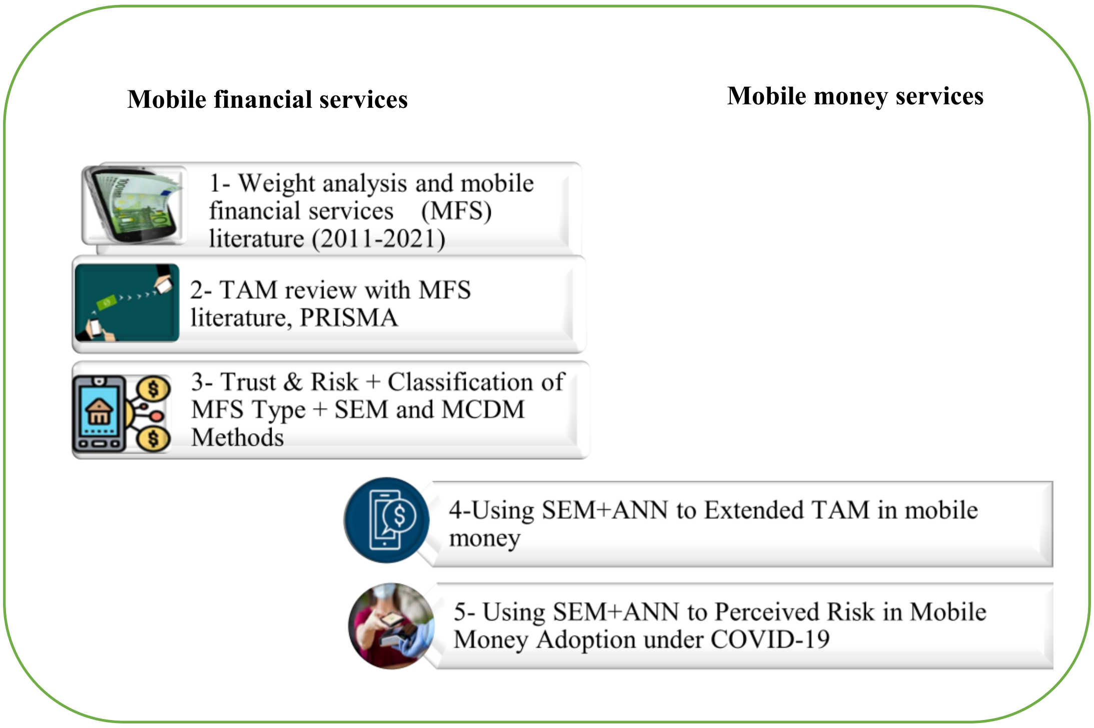

Figure 1-2 List of studies, theoretical models, methodologies, and constructs used
Source: own elaboration

1.5 Dissertation Purpose and Aim

This study explores mobile financial services (MFS) and mobile money services in Togo, focusing on identifying influential factors that impact consumers' intention to adopt these services. It consists of five publications that address various research problems, with each chapter dedicated to a separate study. **Figure 1-3** comprehensively depicts the

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research problems, aims, and scholarly publications associated with pursuing these objectives. **Figure 1-4** illustrates the interconnectedness among the various sections and chapters of the Thesis, emphasizing their coherence.

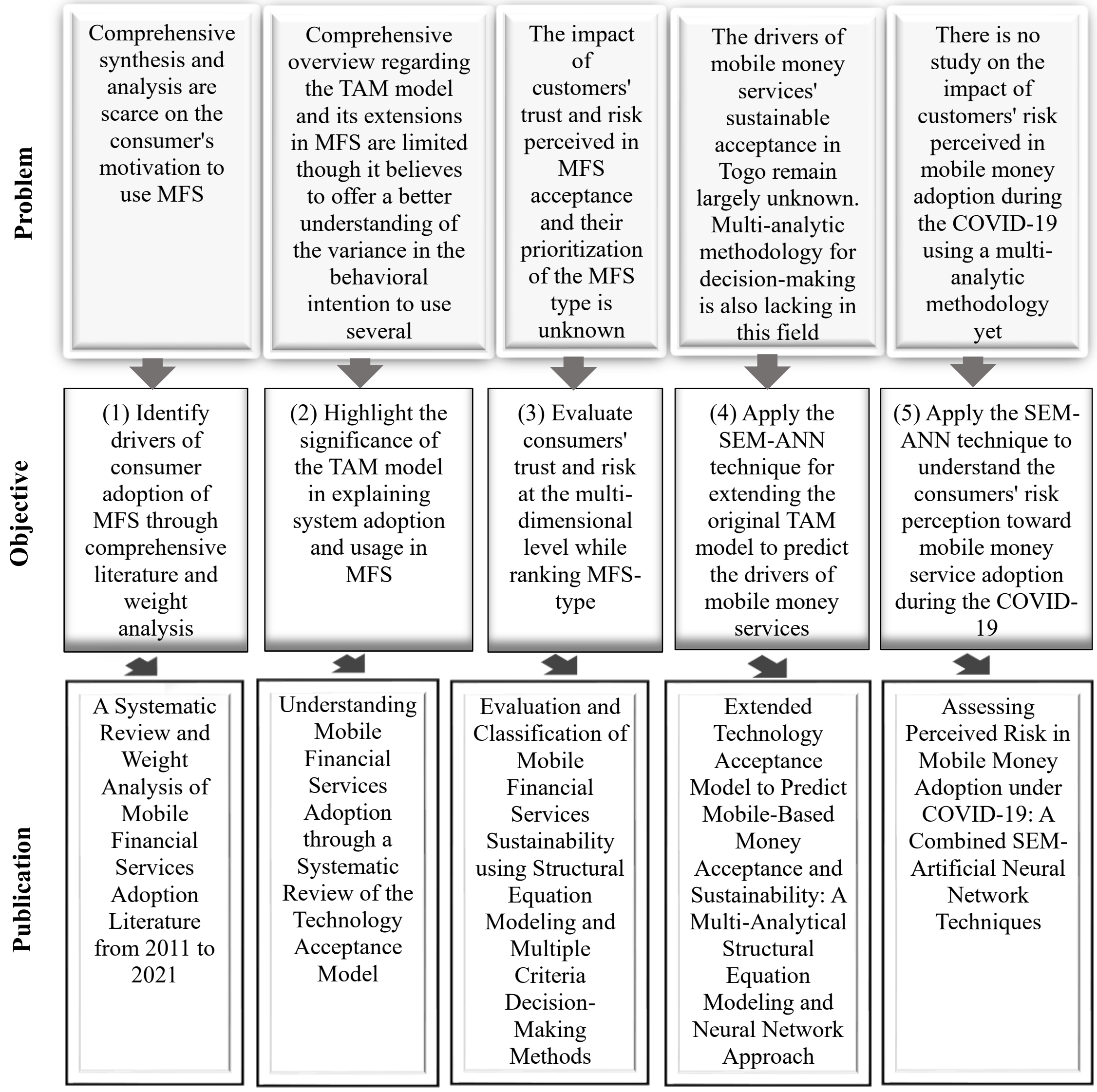

Figure 1-3 Overview of the dissertation structure from the research problems, goals, and publications
Source: own elaboration

The dissertation comprises six main chapters following the introduction chapter (Chapter 1). The dissertation begins from **Figure 1-4** with a systematic literature review (SLR) and weight analysis. This analysis identifies the most commonly used drivers, theories, and models in mobile financial studies over the past decade. Like any typical research project, this work began with a literature review, which is the foundation for the theoretical background reviewed in the subsequent chapters. This exercise helped update the current state-of-the-art knowledge whenever possible. However, due to our schedule, this part of the study was completed last, making it the final component of the overall research paper.

Chapter 3 extensively reviews studies on applying the technology acceptance model (TAM) in the context of mobile financial services (MFS). We analyze various aspects,

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including the drivers of MFS adoption, analysis methods, TAM's progress over the years, countries involved, and sample sizes. The findings highlight the significance of consumers' perception of MFS and the credibility of technology acceptance theories in explaining users' intentions toward adopting new technologies.

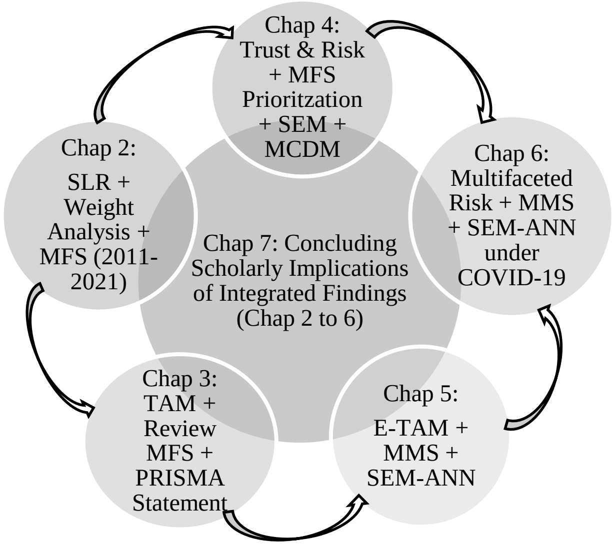
Following the literature review in chapters 2 and 3, the remaining chapters are based on empirical studies (quantitative survey data) in MFS or mobile money services.

In Chapter 4, we examine the multidimensional impact of trust and risk in mobile financial services (MFS), considering both factors' influence on the intention to use MFS and the factors contributing to success and resistance to MFS adoption. Additionally, we categorize different types of MFS based on the preferences of experts and experienced users.

In Chapter 5, we expand the technology acceptance model (TAM) to focus on mobile money services (MMS) specifically. By integrating the conventional constructs of TAM, we identify potential drivers for adopting MMS.

Building upon the findings of Chapters 4 and 5, Chapter 6 examines the adoption of mobile money services from a multidimensional risk perspective during the COVID-19 pandemic using SEM-ANN approach. Due to limited studies utilizing integrated methodologies like structural equation modeling and neural network prediction during this crisis, it presents an exciting area for further research. The chapter highlights the motivation for consumers to engage in contactless activities, including MMS, due to the pandemic's impact on income support and social distancing measures. Assessing various risk factors influencing consumer decisions on MMS adoption during this period becomes crucial.

The dissertation's final chapter summarizes and emphasizes the main conclusions drawn from the preceding chapters. It also analyzes how variations in timing, samples, and scientific methodologies used in the conducted research and publications affect the consistency and compatibility of the results. Additionally, the chapter discusses research contributions and limitations and provides suggestions for future work.



Abbreviations & Acronyms List

ANN	Artificial Neural Network
E-TAM	Extended Technology Acceptance Model
MCDM	Multiple Criteria Decision Making
MFS	Mobile Financial Services
MMS	Mobile Money Services
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
SEM	Structural Equation Modeling
SLR	Systematic Literature Review
TAM	Technology Acceptance Model

Figure 1-4 Thesis Scheme Map
Source: own elaboration

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1.6 Methodology

The research methodology integrates the approach, techniques, and procedures adopted to meet the research objectives, hypothesis, and investigations of concerns. Therefore, it summarizes this thesis's main theories, models, and statistical and mathematical techniques. This process starts with the publications.

1.6.1 Method and Theoretical Frameworks

Regarding the method implemented, we adopted a controlled and structural approach to conducting research by ascertaining a clear research subject, building suitable hypotheses, and embracing an appropriate research methodology (Carson et al., 2001). A specific design using cross-sectional survey methodology was developed and supported in several survey instruments for each research topic in studying mobile financial service adoption. This design aimed to correlate the score of all independent determinants that impact mobile financial services or mobile money acceptance. From The theoretical framework perspective, both the multi-dimensional trust and multi-facet perceived risk model were used in Chapter four, the technology acceptance model (TAM) integrated with self-efficacy, technology anxiety, and personal innovativeness in Chapter five, and the multi-dimensional perceived risk model under COVID-19 in Chapter six.

1.6.2 Quantitative Research Methods

Our research paper on chapters two and three summarizes existing studies on the drivers of MFS acceptance at various levels, using a systematic review approach to ensure that the review process is reliable and replicable. Unlike traditional literature reviews, systematic reviews follow strict guidelines to minimize the impact of subjective judgment and produce a comprehensive review. Reliability is crucial given the importance of review results in informing decisions with significant environmental and socioeconomic implications (e.g.,(Halme et al., 2010)).

To achieve this, chapter two of our paper used a systematic literature review (SLR) methodology, including weight analysis, to analyze MFS adoption literature published between 2011 and 2021. In chapter three, we employed an SLR of the technology acceptance model, following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) statement (Moher et al., 2009) to understand MFS adoption. The PRISMA statement provides an evidence-based approach to identify, screen, select, and include relevant studies in a literature review, ensuring that the review process is transparent and reliable for future research. It is an evidence-based minimum set of items to support researchers refining systematic reviews and meta-analysis reporting.

Chapter four of our study utilized a cross-sectional design to evaluate trust and perceived risk in multi-dimensional decision-making for MFS alternatives in Togo. We used a data set of a two-type survey from March to May 2017, consisting of 538 MFS users (for SEM methodology) and 74 respondents involving only experienced MFS users and experts of MFS (for MCDM methodology). Data were collected from the busiest and most crowded places of the capital town, Lomé, such as Assivito, Dekon, Be, and Université de Lomé-Togo, to ensure a representative sample of potential and current MFS users. We used two phases technique for data analysis where structural equation modeling (SEM) was adopted initially and followed by Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). First, we used SEM to analyze the structural relationships between variables and test hypotheses. Based on J. C. Anderson & Gerbing (1988a) recommendation, the analysis was conducted in two steps, including a reliability and validity assessment of the measurement model and a structural model assessment.

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We used five different fit indices (Browne & Cudeck, 1993), including CFI, TLI, RMSEA, and SRMR, to evaluate the model's goodness of fit.

The SEM-TOPSIS method allowed us to evaluate trust and perceived risk in multi-dimensional decision-making for MFS alternatives while using TOPSIS and AHP to prioritize the output. After applying the SEM technique, we used two multiple-criteria decision-making (MCDM) techniques, TOPSIS and Analytic Hierarchy Process (AHP), to prioritize the output. Developed by C.-L. Hwang & Yoon (1981), TOPSIS is based on the distance between an ideal and non-ideal solution, while AHP is built on weighted aggregation obtained by pairwise comparisons and decision-making preferences (Taslicali & Ercan, 2006). The results of TOPSIS and AHP were consistent and in agreement with each other, with mobile money transfer (MMT) identified as the most appropriate MFS alternative, followed by mobile payment and mobile banking.

In chapter five, the study utilized a method known as SEM combined with ANN (artificial neural networks) to extend the technology acceptance model and predict mobile-based money acceptance and sustainability. This approach was applied to a survey of 539 actual and prospective mobile money users in Lome-Togo between January and February 2019. The theoretical model and guidelines for data analysis were tested using SEM and PLS (partial least square) (J. C. Anderson & Gerbing, 1988). Although SEM is commonly used to verify hypothesized relationships, it may oversimplify complex decision-making processes and detect only linear models. Given that SEM is generally applied to verify hypothesized relationships, it has seldom been integrated with other artificial intelligence algorithms (C. I. Hsu et al., 2009) (T. C. Wong et al., 2011) when users are making technology adoption decisions, as SEM may often oversimplify the complexities involved and merely detect linear models.

To address this issue, ANN was used to model linear and non-linear relationships without necessitating any distribution assumptions (L. Y. Leong et al., 2013). ANN offers more accurate predictions than traditional regression techniques such as MRA, MDA, or SEM (Morris et al., 2003). However, a two-step SEM-ANN approach was used since ANN is unsuitable for hypotheses testing and examining causal relationships (L.-Y. Leong et al., 2013). In the first step, SEM was used to identify significant determinants, and in the second step, ANN was used to build models based only on these determinants. This approach allowed for better in-depth research results than the single-step SEM approach. This study is among the few that combine SEM with ANN to examine mobile money adoption and sustainability in a developing country context.

Chapter six used a survey from Lome-Togo and the SEM-ANN method to examine the supporting model and potential impact of perceived risk on mobile money adoption during COVID-19. The study collected data from 275 respondents between September and November 2021 and adhered to the same SEM-ANN guidelines as in previous studies.

1.7 Thesis Structure

This dissertation is built from a collection of separated research (with slight modification) on interrelated subjects, namely mobile financial services in general and mobile money services to some extent, reported separately. It reveals a synopsis per paper, theories and models adopted, and methods (mainly statistical or mathematical) applied. The studies were reported independently in various chapters, and each has undergone a rigorous double-blinded review process before publication in international journals (see **Table 1-1**).

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Table 1-1 Current studies stage

Chapter	Study name	Theories, models, and methods	Data	Current stage
2	A Systematic Review and Weight Analysis of Mobile Financial Services Adoption Literature from 2011 to 2021	• Systematic literature review (SLR) • Weight analysis	Number of papers: 329 (search results), 207 (filtered), 61 (included)	Published in the Review of Business & Management' TMP
3	Understanding Mobile Financial Services Adoption through a Systematic Review of the Technology Acceptance Model	• A systematic review using the PRISMA statement	Number of papers: 217 (search results), 209 (filtered), 24 (included)	Published in the Open Journal of Business and Management
4	Evaluation and Classification of Mobile Financial Services Sustainability Using Structural Equation Modeling and Multiple Criteria Decision-Making Methods	• Multi-dimensional trust • Multifaceted Perceived risk • SEM • TOPSIS • AHP	538 MFS users with SEM, and 74 both experienced MFS users and experts in Togo for TOPSIS and AHP, Togo	Published in the Journal of Sustainability [SSCI Journal]
5	Extended Technology Acceptance Model to Predict Mobile-Based Money Acceptance and Sustainability: A Multi-Analytical Structural Equation Modeling and Neural Network Approach	• Extended technology acceptance model (TAM) • SEM • ANN	539 actual and prospective users of mobile-based money, Togo	Published in the Journal of Sustainability [SSCI Journal]
6	Assessing Perceived Risk in Mobile Money Adoption under COVID-19: A Combined SEM-Artificial Neural Network Techniques	• Multidimensional perceived risk • SEM • ANN	275 respondents, Togo	Published in the International Journal of Research – GRANTHAALAYAH

SEM: Structural equation modeling, AHP: Analytic hierarchy process, TOPSIS: Technique for order of preference by similarity to an ideal solution, ANN: Artificial neural network.

Source: own elaboration

The thesis's concluding chapter summarizes key findings, compares them to existing research, and highlights the contributions made in chapters two to six. It also acknowledges limitations and suggests future research directions to enhance understanding mobile financial service adoption. Notably, all chapters underwent a rigorous blinded review process and were published in reputable international journals, reflecting a positive indication of the work' quality developed.

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Chapter 2 A Systematic Review and Weight Analysis of Mobile Financial Services Adoption Literature from 2011 to 2021

2.1 Introduction

The rapid rise in the growth of mobile technology worldwide is a phenomenon that has been mainly notable among poor people, primarily due to the prepaid model. Since their importance in disseminating information, particularly the innovations related to mobile money services, mobile technology has been acknowledged worldwide to deliver financial services. With the expansion in the coverage of mobile phone networks and accelerating user growth, mobile financial services have become a powerful channel for the banking industry to offer its customers a wide range of services, overcoming temporal and spatial hindrances. Due to their unique features, such as always-on availability, mobility, and small personalized devices, mobile phones have promptly spread in developed and most developing nations to overcome geographical and socio-economic barriers. Indeed, mobile technology has the potential to allow two primary questions to be addressed simultaneously: from the demand perspective; it represents a possibility for financial inclusion among a population that is underserved by traditional banking services. From the supply angle, it opens up the opportunity for financial institutions to deliver a great diversity of services at low cost to large customers of the poorest sections of society and people living in remote areas.

Mobile financial service (MFS) is a broad term encompassing various financial services that can be conducted on a mobile phone (Gbongli et al., 2020). The typology of mobile financial services entails three leading forms: mobile banking, mobile payment, and mobile money transfer (Gbongli et al., 2020) (FIRPO, 2009). Mobile banking is an additional medium for prevailing customers to interact with the bank. It enables them to open new bank accounts, gain account information, check their balance, block missing cards, transfer funds, obtain branch and ATM locations, and even make financial investments. Mobile payment enables users to make person-to-business payments for goods and services through mobile phones at the point-of-sale terminal or remotely. The customers are gradually using these services as it increases their convenience by excluding the need for coins and cash for small transactions. Mobile money refers to the service that allows users to transfer money between people with less access to bank accounts (M. Kim et al., 2018) (Gbongli et al., 2019). The GSMA (2021) report indicates that in 2020, there are 1.2 billion registered mobile money accounts, 5.2 million unique agent accounts globally, 310 mobile money deployments are live in 96 countries, and a 17 percent year-on-year increase in the accounts (GSMA, 2021). Total mobile money transaction values grew 22 percent in 2020 to \$767 billion. Therefore, the industry is unprecedently processing over \$2 billion daily while having more than doubled in value since 2017. Accordingly, the GSMA expects this value to surpass \$3 billion daily by 2022.

These trends recommend that significant growth opportunities remain, leading to predictions of potentially massive increases in mobile money users. Although mobile money services seem incredibly promising, there is still a need to understand their growth potential and grow this potential fully (Gbongli et al., 2017). Despite such prevalent adoption of smartphones and internet networks, the adoption ratio of mobile financial services is comparatively low (Deb & Agrawal, 2017) (Thakur & Srivastava, 2014) (Gbongli et al., 2020), and the financial industry has faced resistance from customers who

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were skeptical and reluctant to adopt these novel services. Due to these challenges, financial services must continuously assess customers' readiness to adopt technology-based mobile financial to offer adequate services that provide the best value for both the consumer and the service provider.

Several studies use qualitative and quantitative methods to analyze mobile financial services (MFS) and related factors impacting consumer adoption. Despite substantial research on MFS initiatives revealed in international journals across disciplines, there have been scant attempts to provide an integrative model that improves our understanding and explains MFS adoption. Additionally, our examination of the literature background elucidated that the general studies are spread across various areas and contexts in which adoption has been studied. Such fragmented literature makes it challenging for scholars to build upon the existing knowledge and advance the research in the area. Considering the complex nature of MFS as a merging of mobile and financial services, MFS as a focus of research deserves analysis on a broad range of issues surrounding the seamless connection and coordination of these different factors.

To help researchers overcome this challenge, we suggest organizing the literature in the area and critically synthesizing it for future reference. Towards this perspective, the current study proposes to employ the systematic literature review (SLR) methodology and perform weight analysis, which provides an extensive way assessment of the related work and yields numerous advantages as discussed by earlier SLR studies (Behera et al., 2019) (Seth et al., 2020). Based on the weight analysis, the current research will reconcile conflicting evidence and draw a "big picture" in mobile financial services research. The study further proposes highlighting the critical technological factors of using mobile financial services, which contribute to an opportunity for financial services to build the right mobile financial for human needs.

Following earlier systematic review studies, the remaining sections are organized as follows. Section 2.2 offers a brief overview of the methods used to ascertain the relevant research included in this review. Section 2.3 is dedicated to examining the general characteristics of the chosen studies and identifying the significant themes that have emerged from the existing research. In section 2.4, a weight analysis is conducted, and the findings are presented. The subsequent section evaluates the crucial technological factors related to mobile financial services. The study concludes with a discussion of research limitations and possible directions for future research.

2.2 Methodology

We adopted an established research technique for systematic literature reviews to analyze the literature on mobile financial services (MFS) and derive a comprehensive classification of its determinants. A systematic review remains a literature review that intends to answer a formulated question on the topic(s) by finding, describing, and assessing evidence from all published work associated with that question within a particular set of boundaries (Eriksson, 2014). This technique has several advantages over traditional narrative reviews. However, narrative reviews are built mainly on the experience and subjectivity of the author. They generally exclude a section describing the related papers' data sources and localization strategy. This clues to several methodological flaws, especially the non-inclusion of significant contributions, which can bias the author's conclusions (Cipriani & Geddes, 2003) (Fradet12, 2013). Therefore, there is evidence that systematic reviews mitigate chance effects, enhance the legitimacy and authority of the ensuing evidence, and offer more consistent outcomes upon which to

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draw conclusions and make decisions (Waddington et al., 2012) (Fink, 2014). Five steps are generally followed when performing a systematic review of the literature (Booth et al., 2016): (1) formulation of research questions; (2) establishing of inclusion and exclusion criteria; (3) identification of relevant studies; (4) assessment of selected studies; and (5) summary and report of the findings.

2.2.1 Inclusion and Exclusion Criteria

Based on Wu et al. (2021), Inclusion and exclusion criteria were settled to select material related to our study, create a boundary, and limit our methodology's scope. **Table 2-1** displays these criteria and their rationale for inclusion or exclusion.

Table 2-1 Inclusion and exclusion criteria

Criteria	The rationale of the criteria
Inclusion criteria	
Topic: Articles where mobile financial services (mobile financial services, mobile banking/m-banking, mobile payment/m-payment, mobile wallet/m-wallet, mobile money) are explicitly mentioned as the main topic	The present study's central concept is the adoption of mobile financial services. With this criterion, we consider that articles focusing on or related to this topic can be identified
Document type: Empirical and conceptual academic articles published in peer-reviewed journals	This criterion is applied to warrant the quality of the used material (K. Rhaiem & Amara, 2021) and (Voight & Hoogenboom, 2012). It is expected, however, that empirical studies lead to a more sound and relevant comparative analysis
Covered period: 2011-2021	A review of work on Mobile Money and Payment from 2001 to 2011 was conducted by Diniz et al. (2011). Since studies on mobile financial services are recent, the timespan's starting year of publications on this topic was not fixed. This allows us to identify the earliest study on the topics.
Language: English	(K. Rhaiem & Amara, 2021) stressed that 75–90% of total academic articles in the leading scholarly business journals are published in English
Exclusion criteria	
All forms of publications other than research articles published in academic journals	This criterion is adopted due to time and resource limitations. Publications like books, book reviews, conference proceedings, theses, and professional publications were excluded. This criterion enables to include of material published in academic journals merely
Articles written in a language other than English	Though the authors master different languages, the vast mainstream of researchers is likely less exposed to publications in a language other than English. Thus, compared to English published, the articles' potential effect of non-English publications on the academic area is likely to be limited. This criterion is added to exclude articles with abstracts in English, but the main text is written in other languages than English

Source: own elaboration

2.2.2 Search Strategy

Following the earlier works on the adopted procedure (M. Rhaiem, 2017) (K. Rhaiem & Amara, 2021), the crucial keywords were identified based on the authors' expertise and after reading 15 recently published articles in the field of mobile financial services (mobile banking, mobile payment, and mobile money). The electronic search used an adapted query incorporating the Boolean operators "AND" and "OR". The present study used the following keywords to search relevant research outputs using the Scopus database: ("Mobile Financial" OR "Mobile Payment" OR "Mobile Wallets" OR "M-

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Payment" OR "M-Banking" OR "Mobile Banking" OR "Mobile" OR "M-MONEY" OR "MOBILE MONEY") AND ("Adoption" OR "Acceptance") AND ("Financial service"). The performed keyword search returned 329 articles. The subsequent step involved evaluating each article's title, keywords, and abstract to check whether all the inclusion and exclusion criteria were acknowledged. This procedure recommended the exclusion of 122 articles from the list. Several of these rejected articles were concerned more with ATM adoption, m-shopping, app adoption, mobile services in general, and m-commerce, to mention a few. The remaining 207 research papers were passed through quality screening employing the most recent journals' ranking of the ABDC (Australian Business Deans Council) and the ABS (Association of Business Schools). Only papers published in journals ranked (1) as A* (best or leading journal in its field), A (highly regarded journal in the field or subfield), and B (well-regarded journal in the field or subfield) (hence, excluding C and D ranked journals) with the 2022 ABDC journals' ranking or (2) as 4* (world's elite journal), 4 (top journal), 3 (highly regarded journal), and 2 (well-regarded journal) concerning the latest 2021 ABS ranking, were retained. The result of this quality screening led to the elimination of 146 articles. Therefore, 61 articles were booked. Next, an in-depth examination and reading were carried out to further evaluate the retained articles' eligibility. This step confirmed that the 61 included articles matched all the criteria and were eligible for consideration in the systematic review.

2.3 General Characteristics of the Selected Studies and Discussion

2.3.1 Distribution of the Articles by Publication Outlet

Table 2-2 revealed that studies on mobile financial services were published in 13 various journals. With no surprise, The International Journal of Bank Marketing rated first with 8 articles (13.11%), followed by Computers in Human Behavior with 7 publications (11.48%) and to mention a few. Out of the 61 retained articles, 31 (50.81%) were in Information System/ Information Management area, 18 (29.51%) in the Marketing/ Tourism/ Logistics area, 8 (13.11%) in the Management area, 3 (4.92%) in the Marketing area, and 1 (1.64%) in the Finance area. Based on the 2022 ABDC journals' ranking, the majority of articles (30 articles or 49.18%) were published in journals ranked A, whereas only 7 articles (11.47%) were published in journals ranked A*, and 13 articles (21.31%) were published in journals ranked B. There are 5 articles published in four Journals that were not found in the 2022 ABDC journals' ranking but listed under the 2021 ABS journals' ranking. Concerning the 2021 ABS journals' ranking, 24 articles (39.34%) were published in journals classified 1, 28 articles (445.90%) were published in journals classified 2, and 8 articles (13.11%) were published in journals classified 3. Only one article was published in a journal that is not found in the 2021 ABS journals' ranking but was listed in the 2022 ABDC journals' ranking.

Regarding the Analysis of journals by citations, apart from the number of articles, the contribution of a particular journal can also be evaluated by h-index, implying that a number, h, of journal publications, have been cited h times. This measure can be considered one of the genuine indicators for influencing the publishing activity of the journal in the research area under consideration. In this study, the journal with the most impact is the Journal of Business Research, associated with an h-index of 217. An h-index of 217 implies that this number of publications has been cited at least 217 times. **Table 2-2** shows the journals ordered by the number of documents published and the impact measured with the h-index.

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Table 2-2 List of journals with the most productivity and impact on MFS (2011- 2021)

Academic journals	2022 ABDC	2021 ABS	Impact factor	Subject area	Articles	Percentage %	H-Index
International Journal of Bank Marketing	A	1	4.412	MRK, TRM/LG	8	13.11	87
Computers in Human Behavior	A	2	6.829	IS	7	11.48	203
International Journal of Information Management	A*	2	14.098	IS	6	9.84	132
Journal of Theoretical and Applied Electronic Commerce Research	B	1	3.049	IS	3	4.92	33
Australasian Journal of IS	A	1	2.317	IS	2	3.28	22
Journal of E-Commerce Research	B	1	2.861	IS	2	3.28	37
Journal of Islamic Marketing	B	1	3.418	MRK,TRM/LG	2	3.28	43
Journal of Enterprise Information Management	A	2	5.396	IS	2	3.28	67
Journal of Retailing and Consumer Services	A	2	7.135	MRK, TRM/LG	2	3.28	104
Service Industries Journal	B	2	5.7	MRK, TRM/LG	2	3.28	70
Technology Analysis and Strategic Management	B	2	2.874	MGT	2	3.28	72
Technological Forecasting and Social Change	A	3	8.593	MGT	2	3.28	134
Psychology and Marketing	N/A	3	2.939	MKT	2	3.28	124
Transportation Research Part C: Emerging Technologies	A*	N/A	8.089	MRK, TRM/LG	1	1.64	147
Journal of Organizational Computing and Electronic Commerce	A	1	2.571	IS	1	1.64	43
Aslib Journal of Information Management	B	1	1.903	IS	1	1.64	44
Information Technology and Management	B	1	2.627	IS	1	1.64	39
International Journal of Emerging Markets	B	1	2.488	MRK, TRM/LG	1	1.64	32
Journal of Internet Commerce	B	1	3.892	MGT	1	1.64	31
Service Business	B	1	2.791	MRK, TRM/LG	1	1.64	36
Social Responsibility Journal	B	1	2.209	MGT	1	1.64	37
Electronic Commerce Research	A	2	3.747	IS	1	1.64	82
Journal of Computer Information Systems	A	2	3.41	IS	1	1.64	66
Journal of Strategic Marketing	A	2	2.4	MRK, TRM/LG	1	1.64	56
European Management Journal	B	2	5.075	MGT	1	1.64	109
Thunderbird International Business Review	B	2	1.841	MGT	1	1.64	42
Electronic Commerce Research and Applications	N/A	2	6.014	IS	1	1.64	82
International Journal of Retail and Distribution Management	N/A	2	3.771	MKT	1	1.64	87
Information Systems Frontiers	A	3	6.191	IS	1	1.64	73
Internet Research	A	3	6.773	IS	1	1.64	94
Journal of Business Research	A	3	7.55	IS	1	1.64	217
International Journal of Finance and Economics	N/A	3	3.070	FINANCE	1	1.64	41

Notes: Information Systems (IS); Management (MGT); Marketing/ Tourism/ Logistics (MRK, TRM/LG); Marketing (MKT); Not Available (N/A)

Source: own elaboration

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2.3.2. Publication Trend and Investigated Countries

Table 2-3 illustrates the detailed publishing timeline of the studies included. Most studies (52 of 61 or 85.24%) included in this review were published between 2015 and 2021. It is the period where the publication trend has increased to reach, so far, a peak of 14 articles (22.95%) in 2020. Scholars' growing interest in mobile financial services implies that various providers gradually adopt this new service. Therefore, the distribution of the selected empirical studies by country/region showed that the most studied countries are the United States, Spain, and India, with a frequency of 6 each (i.e., 9.83% each) (See **Table 2-4**).

Table 2-3 Authors contributing to the literature on mobile financial services/year

Years	No of articles	Authors
2011	1	(H.-F. Lin, 2011)
2012	5	(Zhou, 2012b), (Yu, 2012), (Al-Jabri & Sohail, 2012), (Peng et al., 2012), (Keramati et al., 2012)
2013	0	N/A (Not Available)
2014	3	(Oliveira et al., 2014), (Goh & Sun, 2014), (Francisco Liébana-Cabanillas et al., 2014b)
2015	8	(E. L. Slade et al., 2015), (Gonçalo Baptista & Oliveira, 2015), (Al Khasawneh, 2015), (E. Slade et al., 2015), (Koenig-Lewis et al., 2015), (Francisco Liébana-Cabanillas et al., 2015), (Di Pietro et al., 2015), (M.-T. Lu et al., 2015)
2016	5	(Tam & Oliveira, 2016b), (Tam & Oliveira, 2016a), (Yen & Wu, 2016), (Oliveira et al., 2016), (Alalwan et al., 2016)
2017	7	(Khalilzadeh et al., 2017), (A. A. Bailey et al., 2017), (A. Gupta & Arora, 2017), (Alalwan et al., 2017), (Goncalo Baptista & Oliveira, 2017), (Changchit et al., 2017), (F. Liébana-Cabanillas & Lara-Rubio, 2017)
2018	4	(Johnson et al., 2018), (Farah et al., 2018), (Francisco Liébana-Cabanillas, Marinkovic, et al., 2018), (Su et al., 2018)
2019	7	(Sujeet Kumar Sharma, 2019), (Raza et al., 2019), (Giovanis et al., 2019), (Baabdullah et al., 2019), (Hussain et al., 2019), (Owusu Kwateng et al., 2019), (Kalinic et al., 2019)
2020	14	(S. Singh, 2020), (Alhassan et al., 2020), (P. Patil et al., 2020), (Suhartanto et al., 2019), (Thusi & Maduku, 2020), (Verkijika, 2020), (Kalinić et al., 2019), (Moorthy et al., 2020), (N. Singh et al., 2020), (Changchit et al., 2020), (Talwar et al., 2020), (J. Zhang & Mao, 2020), (Okello Candiya Bongomin & Ntayi, 2019), (Frimpong et al., 2020)
2021	7	(Jadil et al., 2021), (Wei et al., 2021), (R.-Z. Wu et al., 2021), (Chawla & Joshi, 2021), (Giovanis et al., 2021), (Rafdinal & Senalasari, 2021), (Purohit & Arora, 2021)
Total	61	

Source: own research result

Table 2-4 Geographical scope of studies

Country	Frequency	Country	Frequency	Country	Frequency
USA	6	Indonesia	3	France	1
Spain	6	Pakistan	2	Uganda	1
India	6	Ghana	2	Italy	1
Taiwan	5	Greece	2	Iran	1
Portugal	4	Saudi Arabia	2	Bangladesh	1
UK	3	Indonesian	1	Thailand	1
Malaysia	3	South Korea	1	Brazil	1
Jordan	3	Mozambique	1	Oman	1
China	3	South African	1	Unspecified African Countries	1

Source: own research result

2.3.3 Most Influential Works

Assessing the prolific author offered vital information about the author's contribution and impact on the research areas. Total citations per year compare the article's influence irrespective of the year it was published and are considered important indicators of the articles' influence in MFS adoption behavior. From this end, it was deemed essential to

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identify the highly cited articles and studies that provided novel agendas for the field research. The singularity of the Matthew effect, whereby the researcher tends to cite scholarly articles that are highly cited, is noticeable and is regarded as a better source of information. To uncover the most influential articles published in mobile financial services, we set the cut-off limit to 50 citations and considered only the 20 most highly cited papers between 2011 and 2021. **Table 2-5** lists highly cited mobile financial services papers published in reputed peer-reviewed journals.

The Analysis of the highly cited papers reveals the fact that Alalwan et al. (2017), with the document title "Factors influencing adoption of mobile banking by Jordanian bank customers: Extending UTAUT2 with trust," is the highest number of citations which is 502 citations with Google Scholar Rank (GSRank) 1, significantly contributed towards mobile financial services field, particularly the mobile banking perspective. Their contribution laid the foundation for empirical research works in mobile banking by extending the Unified Theory of Acceptance and Use of Technology (UTAUT2) alongside trust and opened up new vistas of scholarly inquiry. Subsequent to their work, practicing scholars explored the field using established theoretical frameworks, and some scholars even extended the established frameworks by developing and validating new constructs which they felt were largely missing in prior literature (Merhi et al., 2019). Furthermore, some scholars extended the methodological perspective by incorporating advanced statistical analysis in their research (Sujeet Kumar Sharma, 2019).

The next highly cited article in the league has been contributed by Lin (2011). His work also examined the adoption behavior with mobile banking and drew upon innovation diffusion theory and knowledge-based trust literature. The mobile banking service characteristics proposed are used mainly across different studies on mobile financial services in conjunction with established theoretical frameworks. Highly cited research works to aid in attaining theoretical development and methodological maturity and popularity across various disciplines.

Table 2-5 Top 20 Cited documents in the field of mobile financial services

S. No	Authors	Title	Source Title	Cites	Cites Per Year	GSRank
1	(Alalwan et al., 2017)	Factors influencing adoption of mobile banking by Jordanian bank customers: Extending UTAUT2 with trust	International Journal of Information Management	502	100.4	1
2	(H.-F. Lin, 2011)	An empirical investigation of mobile banking adoption: The effect of innovation attributes and knowledge-based trust	International Journal of Information Management	499	45.36	1
3	(Oliveira et al., 2016)	Mobile payment: Understanding the determinants of customer adoption and intention to recommend the technology	Computers in Human Behavior	465	77.5	2
4	(Yu, 2012)	Factors affecting individuals to adopt mobile banking: Empirical evidence from the UTAUT model	Journal of Electronic Commerce Research	422	42.2	1
5	(Oliveira et al., 2014)	Extending the understanding of mobile banking adoption: When UTAUT meets TTF and ITM	International Journal of Information Management	397	49.63	2
6	(Gonçalo Baptista & Oliveira, 2015)	Understanding mobile banking: The unified theory of acceptance and use of technology combined with cultural moderators	Computers in Human Behavior	391	55.86	5

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To continue **Table 2-5** Top 20 Cited documents in the field of mobile financial services

S. No	Authors	Title	Source Title	Cites	Cites Per Year	GSRank
7	(E. L. Slade et al., 2015)	Modeling Consumers' Adoption Intentions of Remote Mobile Payments in the United Kingdom: Extending UTAUT with Innovativeness, Risk, and Trust	Psychology and Marketing	344	49.14	3
8	(Al-Jabri & Sohail, 2012)	Mobile banking adoption: Application of diffusion of innovation theory	Journal of Electronic Commerce Research	252	25.2	3
9	(Alalwan et al., 2016)	Consumer adoption of mobile banking in Jordan: Examining the role of usefulness, ease of use, perceived risk and self-efficacy	Journal of Enterprise Information Management	240	40	11
10	(Khalilzadeh et al., 2017)	Security-related factors in extended UTAUT model for NFC based mobile payment in the restaurant industry	Computers in Human Behavior	228	45.6	1
11	(E. Slade et al., 2015)	Exploring consumer adoption of proximity mobile payments	Journal of Strategic Marketing	175	25	1 5
12	(Tam & Oliveira, 2016b)	Understanding the impact of m-banking on individual performance: DeLone & McLean and TTF perspective	Computers in Human Behavior	167	27.83	4
13	(Koenig-Lewis et al., 2015)	Enjoyment and social influence: predicting mobile payment adoption	Service Industries Journal	160	22.86	1 7
14	(Zhou, 2012b)	Examining mobile banking user adoption from the perspectives of trust and flow experience	Information Technology and Management	153	15.3	5
15	(Francisco Liébana-Cabanillas et al., 2014b)	The moderating effect of experience in the adoption of mobile payment tools in Virtual Social Networks: The m-Payment Acceptance Model in Virtual Social Networks (MPAM-VSN)	International Journal of Information Management	151	18.88	1 8
16	(Johnson et al., 2018)	Limitations to the rapid adoption of M-payment services: Understanding the impact of privacy risk on M-Payment services	Computers in Human Behavior	149	37.25	1
17	(Francisco Liébana-Cabanillas, Marinkovic, et al., 2018)	Predicting the determinants of mobile payment acceptance: A hybrid SEM-neural network approach	Technological Forecasting and Social Change	141	35.25	2
18	(N. Singh et al., 2020)	Determining factors in the adoption and recommendation of mobile wallet services in India: Analysis of the effect of innovativeness, stress to use and social influence	International Journal of Information Management	120	60	1
19	(A. A. Bailey et al., 2017)	Mobile payments adoption by US consumers: an extended TAM	International Journal of Retail and Distribution Management	103	20.6	3
20	(P. Patil et al., 2020)	Understanding consumer adoption of mobile payment in India: Extending Meta-UTAUT model with personal innovativeness, anxiety, trust, and grievance redressal	International Journal of Information Management	96	48	4

Source: own elaboration

2.3.4 Brief Review of The Selected Papers

This section reviews the adoption of various mobile financial services methods by providing some information on theories and models adopted, techniques for collecting and analyzing data, and studied factors influencing use and adoption behavior. However, more detail on theoretical models' occurrences and mobile financial adoption drivers are

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booked in the upcoming section. To ease our understanding, these drivers will be categorized into three perspectives: Technological – Personal – Environmental (TPE).

2.3.4.1. Adoption of various mobile financial payment services/ payment methods

The critical themes acknowledged in mobile financial payment services/ payment methods literature are mobile financial services, mobile payment, mobile banking, mobile wallets, and mobile money. Each theme is discussed below by using examples of related studies. Out of 61 published articles in the last decade (i.e., 2011-2021), 29 research papers (48%) were focused on mobile payment, followed by 27 research papers (44%) on mobile banking. There are only 2 articles published on mobile wallets (3%), 2 articles on mobile money (3%), and 1 article on mobile financial services (2%).

2.3.4.2. Mobile financial payment services

Mobile financial payment services refer to using a mobile phone to access financial services and execute financial transactions. For example, Yen & Wu (2016) predicted the antecedents of continued usage intention of mobile financial services (MFS) in Taiwan. By extending TAM with perceived enjoyment, mobility, and personal habit, the authors further examined the moderating effect of gender on customer relationships. SEM was used for survey data of 368 MFS users. It was found that perceived mobility, personal habit, usefulness, and ease of use were the main antecedents that impact continued usage intention in MFS. However, perceived enjoyment was found to have no statistical significance with intention. Moreover, gender moderates the relationships between the variables in the proposed model. Perceived mobility affecting usage intention will be stronger for men than women, whereas personal habit affecting usage intention will be stronger for women than men.

This section reviews the study on mobile financial service adoption determinants, focusing on perceived mobility and personal habit impacts. Nevertheless, the study has some limitations, which allow fruitful future research. First, because studies on mobile financial services are relatively limited, mainly when considering the various early studies on information technology adoption and innovation diffusion, the theoretical grounds for the relationships among constructs are not robust. Second, while usage intention is used here as a dependent variable, examining the actual usage for future work is advised.

2.3.4.3. Mobile payment

Mobile payment denotes the payments made for goods and services using mobile devices, entailing wireless handsets, personal digital assistants, radiofrequency devices, and near-field communication-based devices (Lei-da Chen & Nath, 2008). Twenty-nine studies out of 61 examined mobile payment in the context of MFS during the last decade.

Four studies focused on India((S. Singh, 2020), (P. Patil et al., 2020), (Purohit & Arora, 2021), (Talwar et al., 2020)). For example, S. Singh (2020) aimed to explain users' post-adoption behavior toward mobile payment systems in India. Data were collected from 370 respondents using the unified theory of acceptance and use of technology (UTAUT) framework and the expectation confirmation model (ECM), with two more constructs: perceived security and trust. It was found that the integrated model has a higher predictive power to explain continuance intentions for mobile payment systems with significant elements of satisfaction, trust, performance expectancy, and effort expectancy.

P. Patil et al. (2020) examined Indian consumer use behavior towards mobile payment using a Meta-UTAUT model adapted as the theoretical lens with personal innovativeness, anxiety, trust, and grievance redressal as extensions. By employing SEM for the data analysis, the empirical examination of the model among 491 Indian consumers found all

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proposed hypotheses to be significant. This study explained 66 % and 50 % variance in behavioral intention and use behavior, respectively.

Purohit & Arora (2021) investigated the factors influencing mobile banking adoption among an emerging market's bottom-of-pyramid (BoP) group. Data were collected from 332 bank customers in the BoP group through a convenient sampling method which was analyzed using structural equation modeling (SEM). It was found that perceived usefulness and ease of use positively influence the attitude toward mobile banking, while the perceived risk and perceived deterrents influence the attitude negatively. The subjective norms and the attitude positively affect mobile banking adoption. Knowledge of mobile banking has a strong effect on ease of use, but it does not influence the perceived usefulness of mobile banking.

The study of Talwar et al. (2020) used cross-sectional data entailing 954 respondents in India to empirically test antecedents and outcomes of initial trust based on the information systems success (ISS) model, transaction cost economics (TCE) theory, and the IT continuance model as theoretical lenses. Using SEM for the analysis, the findings show that Information and service quality positively correlated with initial trust. Initial trust is positively associated with confirmation and perceived usefulness. Perceived usefulness positively correlated with continuation intention.

Four studies also studied mobile payment in the USA ((Khalilzadeh et al., 2017), (A. A. Bailey et al., 2017), (J. Zhang & Mao, 2020), (Johnson et al., 2018)). Khalilzadeh et al.(2017) aimed to assess the determinants of near-field communication (NFC) based mobile payment (MP) technology acceptance by providing an integrated model unified theory of acceptance and use of technology (UTAUT) and technology acceptance model (TAM). The model was tested using structural equation modeling (SEM) with data collected from 412 restaurant customers in the USA. It was found that facilitating conditions do not impact the intention to use NFC-based MP. Social readiness positively impacts the NFC-based MP use in restaurants. Users consider NFC-based MP as fun when they perceive it as useful. Other factors such as attitude, security, and risk are the most influential factors in NFC-based MP usage.

A. A. Bailey et al. (2017) used survey data entailing 240 Midwestern University students in the USA to explore mobile payment adoption by extending the basic TAM with self-efficacy, new technology anxiety, and privacy concerns, particularly tap-and-go payment. By employing SEM, the finding revealed that self-efficacy significantly impacts perceived ease of use and usefulness. These, in turn, impact attitude, which affects the intention to use mobile payment. Privacy concerns also affect attitudes toward mobile payment and behavior intention to use mobile payment. New technology anxiety impacts perceived ease of use but not perceived usefulness. Therefore, this study emphasizes the roles of self-efficacy and privacy concerns.

J. Zhang & Mao (2020) focused on examining the effects of consumer factors on behavioral intention to adopt mobile payments. Building upon the theory of reasoned action (TRA) and technology acceptance model (TAM), a behavioral intention model involving enhanced cognitive, affective, and social antecedents was constructed. Cognitive antecedents include the relative advantage, perceived usefulness and ease of use in the TAM, and technology characteristics (e.g., responsiveness and mobility); affective antecedents emphasize positive and negative emotions related to NFC mobile payments usage. Both antecedents are estimated to affect attitudes. In addition, social antecedents examine subjective norms and the influence of network externalities. Collecting data from 394 adult nonusers of NFC mobile payments in the United States

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and performing SEM analysis revealed that all three antecedents significantly affected individual consumers' intention to adopt NFC mobile payments, explaining a significant amount of variance.

Johnson et al. (2018) investigated the impact of factors influencing m-payment service adoption by applying the diffusion of innovation theory model and exploring the effect of perceived ubiquity, security, and privacy risk. A sample of 270 survey responses collected using convenient sampling and analyzed using PLS-SEM indicated that ease of use, relative advantage, visibility, and perceived security positively impact the individual's intention to use m-payment services. Ubiquity and trialability positively influence the individual's perception of security, while concerns over privacy risks negatively affect perceptions of security. 46.3% of respondents identified themselves as current users of m-payment services, which may suggest a renewed interest on the part of the consumer.

Six articles studied mobile payment in Spain (Kalinić et al., 2019), (Francisco Liébana-Cabanillas et al., 2014b), (Kalinic et al., 2019), (F. Liébana-Cabanillas & Lara-Rubio, 2017), (Francisco Liébana-Cabanillas, Marinkovic, et al., 2018), (Francisco Liébana-Cabanillas et al., 2015)). For instance, Kalinić et al. (2019) examined the moderating impact of gender on the acceptance of peer-to-peer mobile payment systems. A multi-group SEM analysis was used to test the moderating effect of gender by using survey data from 701 Spanish smartphone users. The study acknowledged significant differences between the two observed groups. It identified that men are more likely to use mobile payments than women and are consequently less impacted by the probable risks involved. Furthermore, men are more easily affected by their social environment, while women are more influenced by their innovativeness.

Another study (Francisco Liébana-Cabanillas et al., 2014b) focuses on the moderating effect of experience on intention to use the SMS mobile payment tools on Virtual Social Networks. The proposed research model was built on modifying the classical technological acceptance models (TRA, TAM, and UTAUT) and tested with a survey of 2012 Spain mobile payment users through a quota sampling method. Using the SEM for data analysis, the finding showed that external influences, attitude, usefulness, and risk are determinants of intention to use mobile payment. It was highlighted that previous experience increases intention of use.

Kalinic et al. (2019) aimed to analyze the individuals' usage intention of peer-to-peer (P2P) mobile payment. Using a two-stage approach (SEM and artificial neural network models) for data analysis, the research model is assessed with data collected through an online survey from a sample of 701 respondents in Spain. The findings showed that consumers perceive the usefulness of P2PM-pay as the most crucial factor affecting their decision to adopt this innovative technology. The significant impact of social norms and perceived trust are also corroborated. In comparing the findings of the SEM and the artificial neural network (ANN) analyses, the most significant difference is in the strength of the effect of the two variables, such as security and data protection. The ANN analysis increases the relative importance of perceived trust and perceived risk in the intention to use P2PM-pay. Therefore, the author argued that a multi-analysis approach helps understand model variables' effects.

A study by F. Liébana-Cabanillas & Lara-Rubio (2017) explored the determinants of m-payment from the merchants' perspective using logistic regression and neural network analysis. Based on 151 Spanish merchants for the data set, these different analyses show that the neural network analysis is the most precise tool in this research when predicting

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the use of mobile payment systems in a particular business. The author argued that the probability of adopting mobile payment systems is higher in those companies which find considerable advantages in their adoption.

Francisco Liébana-Cabanillas, Marinkovic, et al. (2018) analyzed the individuals' intention to use NFC m-payment to determine the most relevant variables. To this end, the authors have conducted a study through an online survey of 191 Spanish users of smartphones. Extending the TAM model, the primary data analysis included a two-stage research methodology: SEM and neural network modeling. This study found that perceived usefulness and security were the most significant variables influencing the intention to use. The results of neural network analysis confirmed many SEM findings but also gave a slightly different order of influence of significant predictors.

Francisco Liébana-Cabanillas et al. (2015) assessed users' acceptance of Quick response (QR) code mobile payment systems using a convenient sampling of 168 participants from Spain and extending the TAM framework. The data were analyzed using SEM. It was found that attitude, innovation, and subjective norms are determinants of the future intention to use this technology.

Two articles focus on mobile payment in the United Kingdom (E. L. Slade et al., 2015), (E. Slade et al., 2015). For example, E. L. Slade et al. (2015) studied consumers' adoption intentions of remote mobile payments (RMP) in the United Kingdom by extending UTAUT with innovativeness, risk, and trust. Using survey data from 268 British m-payment respondents and performing SEM analysis, the following results were found: performance expectancy, social influence, innovativeness, and perceived risk significantly influenced nonusers' intentions to adopt RMP, while effort expectancy did not. The inclusion of mobile payment knowledge as a moderating variable showed a substantial difference in the effect of trust on the behavioral intention of those who knew about mobile payment than those who did not.

Another study by E. Slade et al. (2015) explored consumer adoption of proximity mobile payments by extending the UTAUT2 model with trust and risk constructs. Using regression analysis with the data collected from 244 UK consumers, the result reveals that the extended model explains more variance in behavioral intention, but performance expectancy remains the strongest predictor across both models.

Two studies by Peng et al. (2012) and Su et al. (2018) investigated mobile payment in China. For example, Peng et al. (2012) aimed to identify the factors determining tourists' acceptance of tourism m-payment through a survey of 421 tourists in China and tested against the extended TAM using the SEM approach. The empirical finding showed especially strong support for the impact of perceived security, perceived compatibility, destination m-payment knowledge, and tourist susceptibility to interpersonal influence.

Su et al. (2018) investigated how users' Internet experience affects mobile payment adoption. They extended TAM and IDT (Innovation Diffusion Theory) while collecting survey data from 922 mobile users. They examined the mediating effect of five factors, i.e., perceived usefulness, perceived ease of use, compatibility, risk, and privacy concern, in the relationship between Internet experience and mobile payment adoption. The result showed that mobile user data supported the five factors' partial mediating effects.

Only one study regarding mobile payment was conducted in each of the following eleven countries ((Wei et al., 2021), (R.-Z. Wu et al., 2021), (Oliveira et al., 2016), (Verkijika, 2020), (Rafdinal & Senalasari, 2021), (Moorthy et al., 2020), (Koenig-Lewis et al., 2015), (Di Pietro et al., 2015), (Keramati et al., 2012), (Giovanis et al., 2021), (Hussain et al., 2019)). For example, Wei et al. (2021) focused on the young generation's

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mobile payment adoption behavior by extending the UTAUT model with risk perception and bonus/rewards. To this end, 295 samples, with the majority being more tech-savvy, namely generation Y and generation Z in Taiwan, were collected from an online survey in Taiwan, while PLS-SEM and PROHIBIT models were used for data analysis. The empirical results demonstrated the positive effect of social influence on behavioral intention to adopt mobile payment. While behavioral intention and promotional activities are the drivers of the actual usage of mobile payment, perceived risks are found to exert a negative effect, reflecting the risk-averse preferences of the young generation in Taiwan. However, the moderation effect of gender revealed the absence of a gender gap in the use of mobile payment. The findings provide important implications for developing promotion programs motivating the young generation's mobile payment adoption.

R.-Z. Wu et al. (2021) assessed the determinants of the intention to use cross-border mobile payments in Korea among Chinese Tourists. An Integrated Perspective of UTAUT2 with TTF, initial trust model, and task technology fit was applied to 786 Chinese with the experience of using cross-border mobile payment while traveling to South Korea. With SEM analysis for data analysis, the following results were found: initial trust, performance expectancy, effort expectancy, facilitating conditions, price value, task technology fit, and initial trust significantly affect use intention.

Another study by Oliveira et al. (2016) on mobile payment was conducted to understand the determinants of customer adoption and intention to recommend the technology. The authors combined UTAUT2, DOI (diffusion of innovations), perceived security, and intention to recommend in order to build a research model. The model was empirically tested using a survey entailing 301 responses in Portugal and analyzed with the SEM. It was found that compatibility, performance, social influence, and innovativeness influence adoption and the intention to recommend this technology.

Verkijika (2020) aimed to provide an adequate response model for understanding the acceptance of mobile payment systems. In this regard, a model that focuses on understanding the role of emotions (affect, anticipated regret, and anxiety) in accepting mobile payment systems were built. The practical components of the model were adapted from the social-cognitive theory (SCT) and the regret theory. Using a sample of 325 survey responses from South Africa, the finding showed that affect and anticipated regret had a significant positive influence on behavioral intentions to adopt mobile payments, whereas the impact of anxiety was not significant.

A study by Rafdinal & Senalasari (2021) analyzed the adoption of mobile payment applications during the COVID-19 pandemic using the TAM and technology readiness index (TRI). Using collected data from 400 mobile payment users in Indonesia and PLS-SEM to analyze the relationship between variables, the finding revealed that TRI constructs affect perceived usefulness (PU) and perceived ease of use (PEOU), except for discomfort, which has no significant impact on the PU. Further, attitude is influenced by two foremost TAM constructs: PU and PEOU. Meanwhile, the intention to use mobile payment applications is influenced by attitude.

Moorthy et al. (2020) studied the antecedents of behavioral intention to adopt mobile payment among working adults in Malaysia. The constructs of UTAUT2 with perceived security were adopted as a theoretical base. The collected data from 225 participants through a convenient sampling were tested using multiple linear regression (MLR) analysis. It was found that performance expectancy, facilitating conditions, hedonic motivation, and perceived security are significant in mobile payment adoption. However, effort expectancy and social influence are not significant. This result contributed to a

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simple UTAUT2 model with perceived security as an additional construct in explaining the adoption intention of mobile payment.

For example, using SEM for data analysis, Koenig-Lewis et al. (2015) extended TAM and UTAUT by incorporating perceived enjoyment, social influence, knowledge, and perceived risk for understanding mobile payment adoption.

Replications of established theories are tested in a new context of young people's adoption of mobile payment in France. Using an online survey (N = 316), hypotheses were tested based on a comprehensive theoretical framework. The comprehensive model improves earlier models by explaining 62% of the variation in intention to use. Against expectations, perceived ease of use had no significant influence on perceived usefulness and intention to use. The study contributes to advancing understanding of perceived enjoyment which had no direct effect on adoption intention but a significant effect on perceived ease of use and perceived usefulness. Social influence reduces perceived risk, and further contribution is made that perceived enjoyment lowers perceived risk.

Di Pietro et al. (2015) investigated the main predictors of the intention to use mobile payment acceptance with the application to public transport in Italy. The primary reference models, such as the TAM, DOI, and UTAUT, are extended to add new ones tailored to the mobile payment/ticketing framework. The survey of 439 respondents tested the theoretical framework using SEM. The findings revealed that perceived usefulness, perceived ease of use, and the security of the technology influenced the intention to use that technology. Moreover, the perceived usefulness is simultaneously impacted by perceived ease of use, compatibility with users' values and needs, and their attitude toward mobile services. Furthermore, the model confirms the direct relationship between the intention to use technology and its actual usage.

Another study conducted by Keramati et al. (2012) investigated customers' adoption of mobile payment services in Iran. The proposed conceptual model integrated technological and behavioral factors of adopting mobile payment services. With a survey entailing 623 Iranian customers, ANOVA and MANOVA analyses were used to assess the effect of demographic and cultural characteristics on other related research factors. The overall fitness of the proposed model is tested by confirmatory factor analysis and logistic regression. The model revealed that ease of use, usefulness, trust, compatibility, cost, norm, payment habit, availability of mobile phone skills, and convenience are suitable, and these factors influence adoption superiorly.

Giovanis et al. (2021) investigated the adoption of proximity mobile payment services (PMPS) using an extended version of the DTPB. Based on a two-stage hybrid analytic methodology (partial least squares (PLS) regression and artificial neural networks (ANN)), the proposed model was validated empirically using a sample of 951 participants in Greece. The PLS finding indicated that the extended DTPB provides a solid theoretical framework for studying the adoption of PMPS. The results of the PLS-ANN sensitivity analysis agree that interpersonal influence is a more significant factor than external influence, although there were some contradictions regarding the determination of customer attitudes and behavioral intentions toward PMPS usage.

Hussain et al. (2019) aimed to examine m-payment adoption for the bottom of the pyramid (BoP) segment in a developing country context based on a sample size of 247 BoP customers in Bangladesh. By performing confirmatory factor analysis and SEM, the study found that performance expectancy, effort expectancy, facilitating conditions, habit, and social influence significantly influence the BoP segment's behavioral intention. It is shown that performance expectancy, lifestyle compatibility, social influence, and habit

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have relatively more substantial effects and higher predictors of intentions.

Most studies on mobile payment during the past decades used quantitative research methods. The intention to adopt mobile payment was the most researched topic among the discussed studies. It was found that the adoption of mobile payments is influenced the most by attitude, social influence, perceived usefulness, and cognitive antecedents. Among the key factors affecting the non-adoption of mobile payment were lack of privacy and perceived risk. Future research should consider assessing how environmental factors such as social image and payment culture affect adoption. Moreover, moderating variables such as age, education, and experience provide more insights for future research.

2.3.4.4. Mobile banking

Mobile banking enables customers to perform various banking activities using their mobile devices. It is defined as the product or service the financial industry provides using a mobile device, namely a mobile phone, smartphone, or tablet (Gbongli, Peng, et al., 2016) (Shaikh & Karjaluoto, 2014).

Twenty-seven out of 61 studies investigated the adoption and use of mobile banking in countries such as Portugal, Pakistan, Indonesia, Mozambique, South Africa, Malaysia, China, Taiwan, Jordan, Brazil, the USA, Saudi Arabia, Ghana, the UK, and India.

Three studies explored mobile baking in Portugal ((Tam & Oliveira, 2016b), (Tam & Oliveira, 2016a), and (Oliveira et al., 2014)). For instance, Tam & Oliveira (2016b) combined the DeLone & McLean IS success model and the Task Technology Fit (TTF) model to investigate the influence of m-banking on individual performance. Based on a survey questionnaire of 233 individuals in Oman, the data analysis was performed using SEM. The finding revealed that use and user satisfaction are important precedents of individual performance and the importance of moderating the impact of TTF over usage on individual performance. System quality, information quality, and service quality positively affect user satisfaction.

Another study by Tam & Oliveira (2016a) investigated the determinants of mobile banking for individual performance and checked whether or not there are any age or gender differences. A research model was built to address this concern based on the task-technology fit theory to integrate task and technology characteristics, technology usage, and individual performance while relating the age and gender subsamples.

The primary data (a survey of 256 individuals in Portugal) were analyzed using PLS-SEM. The findings revealed that TTF and usage are important precedents of individual performance. The authors found statistically significant differences in path usage to performance impact for the age subsample and no statistically significant differences for the gender subsample.

Another study by Oliveira et al. (2014) synergistically combined the strengths of three IS theories: the task technology fit model, the unified theory of acceptance and usage of technology, and the initial trust model for understanding mobile banking adoption. The model was tested in a study conducted in Portugal. Based on the sample of 194 individuals, partial least squares were performed to test the conceptual model proposed. It was found that facilitating conditions and behavioral intentions directly influence m-banking adoption. Initial trust, performance expectancy, technology characteristics, and task technology fit affect behavioral intention.

Three studies focused on mobile baking in Taiwan ((H.-F. Lin, 2011), (Yu, 2012), (M.-T. Lu et al., 2015)). For example, H.-F. Lin (2011) investigated mobile banking adoption in Taiwan based on innovation diffusion theory and knowledge-based trust literature. Using a survey of 368 participants, both potential customers and repeat customers, the

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research model was analyzed with SEM. The results indicated that perceived relative advantage, ease of use, compatibility, competence, and integrity significantly impact attitude, leading to behavioral intention to adopt (or continue to use) mobile banking. Additionally, based on a multi-group analysis with *t*-statistics, it was found that the antecedents of attitude toward mobile banking differ between potential and repeat customers.

Another study by Yu (2012) employed UTAUT and PLS regression for model analysis to investigate what influences people to adopt mobile banking. Through convenient sampling of 441 respondents in Taiwan, the study empirically concluded that individual intention to adopt mobile banking was significantly impacted by social influence, perceived financial cost, performance expectancy, and perceived credibility in their order of influencing strength. The behavior was considerably affected by individual intention and facilitating conditions. It was further found that gender significantly moderated the effects of performance expectancy and perceived financial cost on behavioral intention, and age moderated the effects of facilitating conditions and perceived self-efficacy on actual adoption behavior.

Very few studies use a technique other than SEM—for instance, M.-T. Lu et al. (2015) adopted multiple attribute decision-making (MADM) models by combining decision-making trial and evaluation laboratory (DEMATEL) with map (INRM), DANP (DEMATEL-based ANP), and the VIKOR method. A conceptual model was developed to explore the user's behavioral intention to adopt mobile banking services in the financial banking industry in Taiwan through DTPB and trust-related behaviors using the knowledge of experts. The study found the following results. Technology-facilitating conditions were the most significant criterion when evaluating mobile banking services in the financial banking industry. It also revealed that information integration and mobile banking services for user behavior intention structure are the most critical information integration areas in mobile banking services development.

Three studies (Alalwan et al., 2017), (Alalwan et al., 2016), (Al Khasawneh, 2015) investigated mobile banking adoption in Jordan. Alalwan et al. (2017) investigated the factors affecting behavioral intention and mobile banking adoption by Jordanian banks' customers. With an extended UTAUT2 model and trust, 343 participants were obtained as data was collected through a convenient sampling while employing SEM for analysis. It was mainly found that behavioral intention is significantly and positively influenced by performance expectancy, effort expectancy, hedonic motivation, price value, and trust.

Alalwan et al. (2016) proposed and examined a conceptual model based on TAM that best explains the key factors influencing Jordanian customers' intention to adopt mobile banking by adding perceived risk and self-efficacy as external factors. The model was tested using SEM with convenient sampling data from 330 Jordanians. The study showed that behavioral intention is significantly influenced by perceived usefulness, perceived ease of use, and perceived risk.

Al Khasawneh (2015) conducted a study to empirically examine consumer adoption of mobile banking in Jordan using a convenient sampling of 268 respondents. The data was performed using SEM by incorporating TAM with perceived trust, perceived credibility, and consumers' attitudes and intentions to use m-banking. The finding revealed that perceived ease of use, perceived usefulness, perceived credibility, and perceived trust significantly positively influence attitude, which positively affects the intention to adopt mobile banking.

Two studies (Raza et al., 2019), (Farah et al., 2018) highlighted the understanding of

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mobile banking adoption in Pakistan. For example, Raza et al. (2019) examined the factors impacting mobile banking acceptance in Islamic banks in Pakistan by using the UTAUT model. The model was analyzed using confirmatory factor analysis and PLS-SEM based on collected data from 229 respondents through convenient sampling. The independent variables were performance expectancy, facilitating conditions, social influence, effort expectancy, perceived value, habit, and hedonic motivation. Behavioral intention was taken as the mediator, and actual usage was used as the dependent variable. The empirical evidence stressed that all the variables except for social influence have a significant positive impact on the intention, which leads to actual usage.

Another study by Farah et al. (2018) studied the critical factors explaining consumer intention and use behavior in mobile banking adoption. Extending UTAUT2 with Non-monetary, Trust, and perceived risk constructs, a convenience sampling technique was used to collect data from 490 respondents in Pakistan. Using SEM for data analysis, the study identified that most of the predictors of intention, such as perceived value, performance expectancy, habit, social influence, effort expectancy, hedonic motivation (except for facilitating condition), perceived risk, and trust, are significant. All predictors of usage behavior are significant.

Two studies used the data collected in Saudi Arabia ((Al-Jabri & Sohail, 2012), (Baabdullah et al., 2019)). For example, Al-Jabri & Sohail (2012) examined factors affecting the adoption of mobile banking in Saudi Arabia. Based on the regression analysis of 330 responses from actual banking users, it was found that relative advantage, compatibility, observability, and perceived risk significantly affect the intention to adopt mobile banking. Trialability and complexity were not found to have a significant effect on adoption. It was found that the proposed model explains 42.8 % of mobile banking adoption based on the Diffusion of Innovation theory.

A study by Baabdullah et al. (2019) identified and examined the most important factors that could predict Saudi customers' continued intention to adopt mobile banking. The proposed conceptual model was built on the TAM and task-technology fit (TTF) model by integrating perceived privacy and security. By using the data of 320 respondents from a convenience sample of Saudi banking customers, the study adopted the SEM technique for data analysis. It was found that the main results supported the impact of perceived privacy, perceived security, perceived usefulness, and task-technology fit on the customers' continued intention to use mobile banking.

While most studies investigated mobile banking adoption in a single country, some studies compared it between developed and developing countries (Changchit et al., 2020), (Frimpong et al., 2020). For example, Changchit et al. (2020) compared mobile banking perceptions among consumers in the U.S. (355 respondents) and in Thailand (400 respondents) using factor analysis and statistical t-tests data analysis. The result found a significant difference in subjects' attitudes toward mobile banking between these two nationalities. On average, the U.S. subjects' attitudes about mobile banking are significantly higher than Thai subjects.

Frimpong et al. (2020) focused on a cross-national investigation of trait antecedents of mobile-banking adoption between the UK and Ghana. Based on insights from innovation adoption and personality research, this study tested a model of mobile-banking adoption using data from a developed and a developing country. Based on convenient and purposive sampling, survey data from 1,340 participants from the UK and Ghana were used for PLS-SEM analysis. The results indicated that intrinsic traits are more substantial in explaining consumers' attitudes toward the services in Ghana than in the UK. However,

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no significant variance between the two countries was observed concerning the mediation effect of consumers' attitudes on the intention to use mobile banking.

Except for the cross-national study, the following eleven countries recorded only a single-country study related to mobile banking. For example, Sujeet Kumar Sharma (2019) identified key antecedents impacting mobile banking acceptance in Oman. The research extends the original TAM by incorporating two cognitive antecedents, i.e., autonomous motivation and controlled motivation, together with trust components for understanding adoption. Data were collected from 225 mobile banking users in Oman and analyzed using an SEM-artificial neural network. It was found that trust and autonomous motivation are the two main predictors influencing mobile banking acceptance.

Another study conducted in Indonesia by Suhartanto et al. (2019) examined mobile banking adoption in Islamic banks by integrating TAM and Religiosity-Behavioral Intention Model. With a sample size of 300 mobile banking customers of Islamic banks from Indonesia, PLS-SEM was applied to assess the association between perceived usefulness, perceived ease of use, religiosity, satisfaction, and adoption. The finding disclosed that integrating TAM and the religiosity-Intention model explains Islamic bank consumers' adoption of mobile banking. Besides perceived usefulness and perceived ease of use, the results emphasize the importance of religiosity in mobile banking adoption

Gonçalo Baptista & Oliveira (2015) study in Mozambique proposed an innovative and comprehensive theoretical model combining UTAUT2 with cultural moderators to offer new insights into factors affecting acceptance and how culture influences individual use behavior. The model was tested using PLS-SEM in a quantitative study conducted with a 252 sample size. Performance expectancy, hedonic motivation, and habit were the most significant antecedents of behavioral intention. To explain mobile banking use behavior, the most important drivers were the effect of habit and culture on intention over use behavior. Collectivism, uncertainty avoidance, short-term, and power distance were the most significant cultural moderators.

Thusi & Maduku (2020) aimed to analyze the determinants of mobile banking app acceptance and use from a sample of 352 millennial retail banking customers in South Africa through convenient sampling. A multi-perspective framework is used based on UTAUT2, multi-dimensional institution-based trust, and risk. The findings suggested that performance expectancy, facilitating conditions, habit, perceived risk, and institution-based trust are significantly associated with the intention to adopt mobile banking apps and that facilitating conditions, perceived risk, and behavioral intention directly influence mobile banking app behavior.

A study by Goh & Sun (2014) used a modified TAM with 105 participants from Malaysia to examine how gender differences influence the adoption of Islamic mobile banking. Using a PLS-SEM, this study revealed two different and remarkable models that impact the acceptance of Islamic mobile banking. Male Muslims desire status and value orientations; therefore, perceived self-expressiveness significantly affects their acceptance of Islamic mobile banking. On the other hand, female Muslims prefer social and utilitarian orientations; thus, their acceptance of Islamic mobile banking was significantly influenced by perceived usefulness and social norms. The author argued that the finding should be interpreted as speculative and not be relied upon to depict behavior in the surveyed communities accurately.

One study by Zhou (2012c) focused on China by examining mobile banking user adoption from trust and flow experience perspectives. With 200 respondents through random sampling, the collected were conducted employing SEM. The finding indicated

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that structural assurance is the main factor affecting trust, whereas ubiquity and perceived ease of use are the main factors influencing flow experience. Trust significantly affects flow experience, and both factors determine usage intention, affecting actual usage.

Giovanis et al. (2019) investigated which of four well-established theoretical models (i.e., TAM, theory of planned behavior, UTAUT, decomposed theory of planned behavior (DTPB)) best explains potential users' behavioral intentions to adopt mobile banking services. The data were performed using SEM based on the convenient sampling of 931 potential users in Greece. The result of the study revealed that the best model is an extension of the DTPB with perceived risk. Customers' attitude, determined by three rationally-evaluated MB attributes (usefulness, easiness, and compatibility), is the primary driver of consumers' intentions to adopt m-banking services. Perceived risk negatively affects attitude formation and inhibits willingness to use m-banking services.

One study by Goncalo Baptista & Oliveira (2017) in Brazil identified the potential impact of using game mechanics and game design techniques in accepting mobile banking services. The theoretical model based on UTAUT was tested in a quantitative study using SEM with 326 entailing actual local banking customers in Brazil. The findings showed a direct and strong relationship between gamification and intention to use mobile banking services. This supports that gamification can help make banking activities more exciting, engaging, and enjoyable when used and designed appropriately, increasing customer acceptance, engagement, and satisfaction.

For instance, Changchit et al. (2017) examined the determinants of attitudes toward using and accepting mobile banking in the USA. With a convenient sampling, 309 students enrolled at a southwestern United States university participated in this study using multiple regression techniques for data analysis. Besides perceived usefulness and perceived ease of use included in the original TAM model, the modified model involved five additional factors (perceived privacy, perceived security, previous experiences, normative beliefs, and technology competency) as determinants of attitude toward mobile banking usage. It was found that perceived usefulness, perceived ease of use, perceived security, and previous experiences were key determinants for whether subjects intend to use mobile banking.

One study by Owusu Kwateng et al. (2019) examined factors influencing customers to adopt and subsequently use m-banking services in Ghana using the UTAUT2 model with age, educational level, user experience, and gender as moderators. With a purposive sampling of 300 users of m-banking services in Ghana, the primary data collected were analyzed using PLS-SEM. Findings indicated that habit, price value, and trust are the main factors influencing adopting and using m-banking in Ghana. Individual differences in gender, age, educational level, and user experience responded in a different way as they moderate the relationship between UTAUT2 constructs and use behavior.

A. Gupta & Arora (2017) investigated the adoption of mobile banking among Indian consumers using the framework of behavioral reasoning theory (BRT) to hypothesize relationships between values, reasoning constructs, attitudes, and intentions. With the collected data from 379 Indian banking consumers, confirmatory factor analysis and SEM were used to analyze the data. It was found that "reasons for" and "reasons against" impact m-banking adoption. Regarding the "reasons for" m-banking adoption, ubiquitous was the primary determinant, and among the "reasons against" m-banking adoption, the tradition barrier was the primary determinant. The findings also confirmed that the value of "openness to change" significantly influences reasons for adoption and has no impact on reasons against and attitudes toward m-banking.

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The studies on mobile banking mainly focused on antecedents of acceptance and use of mobile banking and customer attitude. Although the above studies offered valuable insights into the mobile banking industry using theories such as TAM, UTAUT2, and DTPB models, they have some limitations that provide future research directions. First, no qualitative study was performed by the researchers of this literature review. Indeed, all the surveys were conducted by questionnaire, and no data collection was done by interview. Future research could adopt a qualitative approach or a combination of quantitative and qualitative approaches to better understand consumer behavior regarding mobile banking. Second, most studies adopted convenience sampling techniques, limiting the generalizability for the entire population. Therefore, it is suggested that future research study different demographic groups within the target population (Farrokhi & Mahmoudi-Hamidabad, 2012). Third, most studies focus on a single country or even a city, and few comparative studies have been conducted in this literature review. Indeed, out of 26 studies regarding banking adoption, only two have recently opted for cross-national research, as Changchit et al. (2020) conducted a study between the United States and Thailand, while Frimpong et al. (2020) opted for UK and Ghana. This kind of work would allow us to measure the impact of cultural factors on mobile banking adoption.

2.3.4.5 Mobile wallet

Mobile wallet refers to remote payment technologies which need to be installed in the smartphone to allow the consumer to store his money and perform transactions directly from the wallet (Madan & Yadav, 2016). Interestingly, only two studies out of 61 focused on mobile wallets, and they were conducted in India (Chawla & Joshi, 2021), (N. Singh et al., 2020). For example, Chawla & Joshi (2021) aimed to enhance the performance of attitudes toward mobile wallet adoption among Indian consumer segments. Integrating TAM and UTAUT, a nationwide survey was conducted to obtain 744 responses based on convenience sampling. Primary analyses were performed using one-way Analysis of Variance (ANOVA) and Importance-Performance Map Analysis (IPMA). The finding regarding each cluster indicated that the top three critical constructs are perceived usefulness, security, and lifestyle compatibility, as indicated by the IPMA.

A study (N. Singh et al., 2020) explored factors influencing users' recommendations to use m-wallet in India. Combining the TAM and UTAUT2 to develop the study model included 206 responses in India and SEM technique for data analysis. It was found that ease of use, usefulness, perceived risk, and attitude significantly affect the user's intention, which further influenced the users perceived satisfaction and recommendation to use mobile wallet services. The study also determined the moderating effect of stress and social influence on user satisfaction and recommendation.

Research on mobile wallets focused on factors affecting adoption and customer satisfaction. The following limitations can be underlined based on the above overview of the studies. First, the studies did not test for the effect of age, gender, and education as potential factors affecting mobile wallet adoption. Future research should include these variables in their proposed models. Second, because the two studies focused on India, thus data were collected from respondents living in India. From this perspective, studying mobile wallets at the cross-national level can provide additional insight into mobile wallet adoption and satisfaction.

2.3.4.6 Mobile Money

Mobile money is a digital payment platform that transfers money between cellphone devices. Alhassan et al. (2020) studied consumer acceptance and continuance of mobile

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money in Africa using secondary data with the TAM model and employed SEM for data analysis. The research model tests the context-based constructs to determine how these constructs affect peoples' intentions and attitudes toward the continued use of mobile money. The results suggested that the availability of electricity remains an essential factor for mobile phone functionality and continuing use of the service in the long run. It also found a correlation between regulations perceived as enabling and individuals' intentions to continue using mobile money. However, a negative correlation exists between rural dwellings and individuals' intentions to use mobile money.

Okello Candiya Bongomin & Ntayi (2019) aimed to establish the mediating effect of trust in the relationship between mobile money adoption and usage and financial inclusion, focusing on rural Uganda. A quantitative survey based on 379 micro, small and medium enterprises (MSMEs) located in northern Uganda was analyzed using PLS-SEM. The authors found evidence that trust increases mobile money adoption and usage to raise the scope of financial inclusion of MSMEs in developing countries. Moreover, when the individual effect was determined, trust also had a significant and positive effect on financial inclusion.

The studies on mobile money generally focused on enablers and the inhibitors of mobile money adoption and customer satisfaction. Based on the above overview of the studies, the following limitations can be underlined. The studies did not test for the effect of age, gender, and education as possible elements impacting mobile money adoption. Future studies are encouraged to include these variables in their proposed models.

2.3.5. What are the Analytical Techniques that underpin the Studies of MFS?

The majority of studies (47 articles or 77.04%) on mobile financial services used structural equation modeling (SEM) and partial least square (PLS) as the main tools of analysis. For the last two decades, SEM has become the most commonly employed technique for many scholars investigating complex relationships between latent constructs (Astrachan et al., 2014). However, with the increasingly challenging requirements of covariance-based SEM (CB-SEM) in terms of distribution assumptions, sample size, and model complexity (Astrachan et al., 2014) (Joseph F. Hair et al., 2014), the use of the partial least squares SEM (PLS-SEM), a less restrictive method, is enjoying widespread popularity and success with academicians (Souiden et al., 2019). PLS-SEM applications have grown exponentially in the past decade (Leguina, 2015), especially in the social sciences (e.g., (Ali et al., 2018) (Ringle et al., 2020)), and its use is expanding in marketing (Kumar et al., 2020) (Buzeta et al., 2020) (Gbongli et al., 2019) and information system research (Wynne Chin et al., 2020). Artificial neural network analyses were conducted in five studies (8.19%), and regression or multiple regression analyses were used in four articles (6.55%). In contrast, a few studies used other techniques such as MADM (multiple attribute decision-making), k-means clustering, ANOVA (analysis of variance), MANOVA (multivariate analysis of variance), t-tests, and IPMA (importance-performance map analysis). It is essential to mention that the cross-sectional data design is the most used approach. Longitudinal and panel designs are nonexistent, signifying the potential difficulties of these methods to be carried out in the marketing discipline in general and in the financial sector. As for the qualitative approach, none of the studies were found using it.

2.3.6 What is the Theoretical Basis that Supports the Studies of MFS?

Most earlier studies examining consumers' adoption of mobile financial services rely on well-established models to explain consumers' behavior or behavioral intention.

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Among these models, the unified theory of acceptance and usage of technology (UTAUT/UTAUT2) was one of the main theoretical frameworks in 25 articles (40.98%), followed by the technology acceptance model (TAM) used in 23 studies (37.70%). The remaining are the task technology fit model (TTF) adopted by 5 studies (8.19%), the theory of planned behavior (TPB)/the decomposed theory of planned behavior (DTPB) adopted in 5 studies (8.19%), and the innovation diffusion theory (IDT)/diffusion of innovation (DOI) considered by 4 articles (6.55%). Additionally, other behavioral models were considered either solely or combined with the innovation adoption models to explain consumers' adoption of mobile financial services. Among these models, we can indicate the theory of reasoned actions (TRA), the initial trust model (ITM), the expectation confirmation theory (ECT), the IT continuance model of Information systems success (ISS), the model of transaction cost economics (TCE) theory, the social-cognitive theory (SCT), and the regret theory.

2.3.7 Factors affecting Behavioral Intention of Mobile Financial Services

The factors affecting behavioral intention to adopt mobile financial services can be viewed in **Table 2-6** as considering the total of significant columns. For example, the most studied variable was performance expectancy (14 times, i.e., 22.95%) (Oliveira et al., 2014), (Raza et al., 2019), (Moorthy et al., 2020). It is followed by social Influence (21.31%) (Khalilzadeh et al., 2017), (Farah et al., 2018), (Hussain et al., 2019), (Koenig-Lewis et al., 2015), attitude (14.75%) (Francisco Liébana-Cabanillas et al., 2015) and along with others. Additionally, just a few studies found a significant impact of task technology fit (R.-Z. Wu et al., 2021), initial trust (R.-Z. Wu et al., 2021), gamification impact (Goncalo Baptista & Oliveira, 2017), and perceived enjoyment (Kalinic et al., 2019) on behavioral intention.

2.4 Weight Analysis

This study uses the vote-counting method (M. Rhaiem, 2017), which reports the number of times a concept is used and the number of times it is statistically significant to demonstrate its relevance. In particular, the study focuses on weight analysis, which examines the strength of a predictor (independent variable) on the outcome (dependent variable). This analysis enables for investigation of the predictive power of an independent variable in a studied relationship (Jeyaraj et al., 2006). **Table 2-6** briefly describes the 33 most frequently used relationships towards behavioral intention to use mobile financial services. This involves the number of significant and non-significant relationships, the number of relationships examined by earlier research between each pair of dependent and independent variables, and the weight calculated for each of these relationships. Therefore, most studies used behavioral intention as a dependent variable (33 times). To perform weight analysis, the number of significant relationships was divided by the total number of analyzed relationships between an independent and dependent variable (Ismagilova et al., 2020). The weight 1 (one) indicates that the relationship between the two constructs is significant in all studies, whereas 0 (zero) indicates the opposite, that it is non-significant across all (Jeyaraj et al., 2006). For example, the weight for the relationship between performance expectancy and behavioral intention is calculated by dividing 14 (the number of significant relationships) by 16 (the total number of relationships), which equals 0.875. According to Jeyaraj et al. (2006), predictors can be categorized into "well utilized" (studied more than 5 times) and experimental (examined less than 5 times). A well-utilized predictor is regarded as the

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best predictor if its weight equals more than 0.8. A predictor is viewed as promising if examined less than five times (experimental), and its weight equals 1.

Following the weight analysis, it was found that well-utilized predictors for behavioral intention are social influence (examined 19 times), performance expectancy (examined 16 times), effort expectancy (examined 14 times), facilitating condition (examined 9 times), hedonic motivation (examined 12 times), habit (examined 8 times), perceived risk (examined 7 times), trust (examined 6 times), perceived ease of use (examined 8 times), perceived security (examined 5 times), perceived usefulness (examined 6 times), social norms (examined 7 times), and attitude (examined 9 times). Out of these well-utilized predictors, six predictors, namely attitude (weight equals 1), perceived ease of use (weight equals 1), performance expectancy (weight equals 0.875), habit (weight equals 0.875), social norms (weights equals 0.857), and perceived usefulness (weight equals to 0.833), are considered as the best predictors of behavioral intention.

There are 18 predictors of behavioral intention, which are experimental: Perceived Value (examined 4 times), Price Value (examined 4 times), and Trust (examined 4 times), to name a few. Out of 18 experimental predictors, except trust, seventeen are promising with a weight of 1. Social Influence, Hedonic Motivation, Effort Expectancy, facilitating condition, and perceived risk are considered the least effective predictors of behavioral intention, as they were studied more than five times with a weight less than 0.8.

Table 2-6 Result of weight analysis

Independent Variable	Dependent Variable: BI (Behavioral Intention)	Total of significant	Total of non-significant	Total No of test	Weight	*Independent Variable*	*Dependent Variable: BI*	*Total of significant*	*Total of non-significant*	*Total No of test*	*Weight*
Performance Expectancy	BI	14	2	16	0.875	*Perceived credibility*	BI	*2*	*0*	*2*	*1*
Social Influence		13	6	19	0.684	*Perceived behavioural Control*		*2*	*0*	*2*	*1*
Attitude		9	0	9	1	Personal Innovativeness		2	0	2	1
Hedonic Motivation		8	4	12	0.667	Usage Intention		1	0	1	1
Perceived Ease-of–Use		8	0	8	1	Task Technology Fit		1	0	1	1
Habit		7	1	8	0.875	Initial Trust		1	0	1	1
Facilitating conditions		5	4	9	0.556	Visibility		1	0	1	1
Perceived Risk		5	2	7	0.714	Institution-based trust		1	0	1	1
Subjective Norms		6	1	7	0.857	Lifestyle compatibility		1	0	1	1
Perceived security		*5*	*0*	*5*	*1*	*External influences*		*1*	*0*	*1*	*1*
Perceived usefulness		*5*	*1*	*6*	*0.833*	*Gamification impact*		*1*	*0*	*1*	*1*
Perceived Value		*4*	*0*	*4*	*1*	*Knowledge*		*1*	*0*	*1*	*1*
Trust		*4*	*2*	*6*	*0.667*	*Perceived self-expressiveness*		*0*	*1*	*1*	*0*
Innovativeness		*2*	*0*	*2*	*1*	*Perceived Enjoyment*		*0*	*1*	*1*	*0*
Relative advantage		*2*	*0*	*2*	*1*	*Individual Mobility*		*0*	*1*	*1*	*0*
Perceived financial cost		*2*	*0*	*2*	*1*	*Visibility*		*1*	*0*	*1*	*1*

Source: own research result

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2.5 The Critical Technological Drivers of Mobile Financial Services

2.5.1 The Technological – Personal – Environmental (TPE) Framework Mapping

Researchers adopt no fewer than 21 factors to assess mobile digital financial services. **Table 2-7** presents the 38 drivers (factors) influencing humans using mobile financial services (MFS). The ten (10) most studied drivers of MFS are perceived usefulness, perceived ease of use, facilitating condition, social influence, performance expectancy, effort expectancy, attitude, trust, habit, and social norms. Based on **Table 2-7** (i.e., the column of number (No)), **Figure 2-1** displays the mapping of the Technological – Personal – Environment framework, which entails 38 factors mapping to the three significant area variables. Added areas represent the various intersection between technological–personal, technological–environment, personal–environment, and all of the variables (see **Figure 2-1**). The numbers used in **Figure 2-1** refer to the list of factors in column number (No) in **Table 2-7** (e.g., 1 is perceived usefulness, 2 is perceived ease of use).

Table 2-7 Occurrences of mobile financial services factors

No.	Considered variables as drivers of MFS adoption	No of Time	*No.*	*Considered variables as drivers of MFS adoption*	*No of Time*
1	Perceived Usefulness	24	20	Risk	3
2	Perceived Ease of–use	23	21	Perceived Credibility	3
3	Facilitating Conditions	20	22	External Influence	3
4	Social Influence	20	23	Cost	2
5	Performance expectancy	19	24	Structural Assurances	2
6	Effort expectancy	18	25	Firm Reputation	2
7	Attitude	16	26	Privacy Risks	2
8	Trust	14	27	Knowledge	2
9	Habit	10	28	Perceived Enjoyment	2
10	Subjective Norms	10	29	Rural Dwelling	1
11	Price Value	4	30	Education	1
12	Perceived Security	7	31	Religiosity	1
13	Satisfaction	6	32	Institution-based Trust	1
14	Self-efficacy	6	33	Anticipated Regret	1
15	Personal Innovativeness	6	34	Reasons for Adoption	1
16	Technology Characteristics	4	35	Reasons against Adoption	1
17	Relative Advantage	4	36	Optimism	1
18	Task Technology	3	37	Gamification Impact	1
19	Anxiety	3	38	Individual Performance	1

N.B. Detail on each paper reference used in **Table 2-7** is provided in the author's published paper related to Chapter 2

Source: own research result

The critical technological factors of mobile financial services adoption proposed as one of the objectives for the research can be deduced from **Figure 2-1**. The personal factor is the prevalent factor supporting mobile financial services' existence. In addition to personal factors, the second most significant factor is technological, with as many as six factors. Even there are 5 factors included in the technological-personal area. The small factor that researchers employed is the environmental factors. This is because the environmental factors are located at the research site, so they cannot generally be changed. Three environmental factors are structural assurances, rural dwellings, and social influence. The situation can be of concern for the development of technology, especially mobile financial services when considering the factors found in the technological factor, namely 6 factors: facilitating condition, Perceived Security, Technology Characteristics, Task technology, Perceived credibility, and Firm reputation. Apart from these 6 factors,

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there are factors that, together with personal factors, are 7: compatibility, value, services, accessibility, system quality, agreement, and usability. In addition, there are 2 factors related to technological, personal, and environmental factors are considered in the development of technology: structural assurances and knowledge. These 13 factors are, therefore, very beneficial for technological development, particularly in mobile digital financial services, when developing and improving the services.

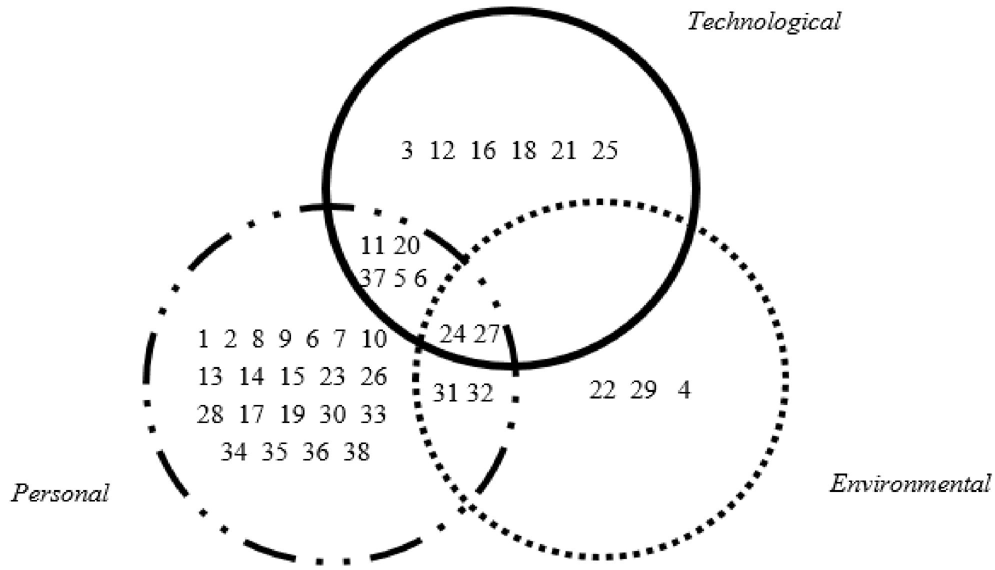

Figure 2-1 Mapping of TPE framework
Source: own elaboration

2.6 Conclusion

This study aimed to offer a comprehensive literature review and weight analysis. In order to achieve this aim, 61 studies that focused on mobile financial services methods published during the last decades (2011-2021) were collected and assessed. The following implication for research and practice and conclusions can be drawn based on the results.

Most studies emphasized factors impacting the intention to adopt mobile digital financial services employed UTAUT and TAM as theoretical foundations. Specifically, our study makes theoretical contributions: It provides a deep insight into the theories and methods utilized by earlier scholars. For instance, it reveals that the unified theory of acceptance and usage of technology (UTAUT/UTAUT2) is the most popularly applied theory for consumer behavioral intention in the existing literature on mobile financial services and payment methods, followed by the technology acceptance model (TAM) and the task technology fit model (TTF). These findings can help in the development and enrichment of theory-based study by patronizing academicians to ascertain the theories and frameworks that have proven validity and are valuable enough to be taken forward for investigating the adoption of various digital financial innovations.

The most used constructs in literature were acknowledged, and their relevance was underlined, providing an update on current state-of-the-art knowledge. For researchers, this study offers strong support and a complete vision of the most significant variables already investigated at the individual level on mobile financial service adoption. It presents an integrated theoretical model that may be employed to further improve

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individual acceptance models as a starting point for future study. For practitioners, understanding the leading constructs and relationships between variables is essential for designing, refining, and implementing mobile financial services that can achieve high consumer acceptance, reinforcing current levels of adoption.

Among 16 well-utilized predictors examined using weight analysis, only six (attitude, perceived ease of use, performance expectancy, habit, social norms, and perceived usefulness) emerged as strong predictors for intention to adopt.

Additionally, a systematic literature review identified 33 key factors influencing the use of mobile financial services in financial institutions. Within the 38 keys, 11 critical technological factors can be used to design, improve and adjust current mobile financial services with technology conditions. It can therefore become tools to help customers meet the requirements of financial institutions. Therefore, researchers can deduce the variables to be chosen for analyzing consumers' intention to adopt and use behavior toward mobile financial services and payment methods.

2.7 Limitations and Future Research Directions

While this study summarizes and extends knowledge focus on mobile financial services and payment methods, some limitations exist. The first ascends from the failure of an initial plan to assess the relationships between the reviewed studies' dependent and independent constructs and offer prediction strengths for each. However, in most studies, the data analysis section only involved tests of those paths the authors had examined, making it challenging to perform the further analysis needed to attain the planned purpose. For future literature reviews, it is advised that authors consider this issue during their screening process if they wish to carry out a comprehensive meta-analysis. Second, the studies for this research were collected only from Scopus, which limited the number of studies accessible for review and weight analysis. Future research should use a broader range of databases. Third, we followed a robust study search protocol grounded on relevant keywords, yet some studies associated with mobile financial services and payment methods could have been missed because of the absence of our keywords in their title, author keywords, and abstract. Despite these limitations, this is the first comprehensive study of factors affecting the adoption and use of mobile financial services, and payment methods focused on the last decades, which provides theoretical and practical directions.

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Chapter 3 Understanding Mobile Financial Services Adoption through a Systematic Review of the Technology Acceptance Model

3.1 Introduction

The increasing use of mobile devices via Internet networks has brought several opportunities for mobile financial services (MFS) (Ha et al., 2012). The mobile Internet penetration rate is predicted to reach 71% of the world's population by 2025 (GSMA, 2018). Mobile financial services have become an appealing research trend for many scholars (Giovanis et al., 2021) (Gbongli et al., 2020), (Gbongli, 2017). The typology of mobile financial services entails three leading forms: mobile banking, mobile payment, and mobile money transfer (Gbongli et al., 2020) (FIRPO, 2009). With the advanced and dynamic development of technologies such as MFS, how fast the consumers accept these technologies depends on several factors, including the availability of technology, convenience, speedy transactions, security, and many others. There have been several researchers addressing the consumers' adoption of new technologies (Deb & Agrawal, 2017), (Hussain et al., 2019) (E. L. Slade et al., 2013) (LAI, 2016). Such as is the case with other technologies, mobile financial services technologies were examined using different technology acceptance models and theories. This is because those theories and models provide a better understanding of the users' behaviors toward a specific technology or service through the factors supporting them (Al-Maroof et al., 2022). It is believed that identifying these factors would enhance the effectiveness of MFS by enabling researchers to examine those factors and users' readiness to use MFS.

In order to comprehend the drivers of MFS adoption, some theoretical models were applied, entailing the "theory of reasoned action (TRA)" (Fishbein & Ajzen, 1975), "technology acceptance model (TAM)" (Davis, 1989), "unified theory of acceptance and use of technology (UTAUT)" (Venkatesh et al., 2003a), and "theory of planned behavior (TPB)" (Icek Ajzen, 1985), among many others. Among those, the TAM was regarded as one of the most commonly used theoretical models for predicting the adoption of several technologies due to its simplicity, adaptability, and soundness (King & He, 2006). More specifically, the TAM was recently found to be the most frequently used theoretical model for understanding mobile banking adoption (Souiden et al., 2020). It was also argued that TAM has efficient explanatory power and has been validated through several measurement scales (Venkatesh & Bala, 2008). The solid empirical support of TAM to its core variables, namely "perceived ease of use" and "perceived usefulness" in examining the individuals' adoption of several technologies, increased the applicability of the model across different disciplines (Alhassan et al., 2020), (Al Khasawneh, 2015), (Al-Qaysi et al., 2020) (Gbongli et al., 2019).

In line with the surveyed literature, many review studies were conducted to understand the applicability of TAM from the mobile financial perspective by examining several issues. Although each of those studies offered a valuable synthesis of TAM, further issues are still disclosed and call for further investigation. Therefore, this paper offers a systematic review of existing TAM-based MFS studies to identify the factors affecting MFS adoption. Moreover, this systematic review also expects to examine the surveyed studies by considering other issues, comprising analysis research methods, TAM progress over publication years, participative countries, and sample size. Stemming from this aim, the authors intend to answer the following research questions.

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RQ1: What are the most frequent drivers of MFS adoption? RQ2: What are the dominant analysis research methods in assessing TAM-based MFS studies? RQ3: What is the progress of TAM-based MFS studies over publication years? RQ4: What are the most active countries in conducting TAM-based MFS studies? RQ5: What research sample size and method were used in the analyzed TAM-based MFS studies?

3.2 Method

This study employs a systematic review technique for reviewing published research studies on using TAM in the context of mobile financial services. We incorporate the well-known principle guidelines (Kitchenham, 2007) put forward in conducting systematic review studies and other relevant systematic reviews in the domain (Al-Saedi et al., 2019). These procedures were strictly followed as per the subsequent subsections.

3.2.1 Inclusion and Exclusion Criteria

Inclusion and exclusion criteria were settled for the critical analysis of the articles related to our study to create a boundary and limit our methodology's scope. **Table 3-1** displays these criteria and their rationale for inclusion or exclusion.

Table 3-1 Inclusion and exclusion criteria.

Inclusion Criteria	Exclusion Criteria
Must contain mobile financial services (i.e., mobile banking, mobile payment, mobile money, mobile wallet) as an essential technology	TAM-based studies but not mobile financial services (MFS)
Must contain the TAM as a theoretical model.	MFS-based studies but not TAM
Must be written in English language only	Articles written in a language other than English
Accessibility to full-text articles.	Inaccessibility to full-text articles.
Must be published between 2011 and 2021.	Articles published earlier than 2011 or after 2021.
Empirical and conceptual academic articles published in peer-reviewed journals	All forms of publications other than research articles published in academic journals

Source: own elaboration

3.2.2 Data Sources and Search Strategies

The research studies used in the current systematic review were collected between 2011 and 2021. The electronic search was performed using an adapted query incorporating the boolean operators "AND" and "OR". The present study used the following keywords to search for the targeted studies based on the Scopus database: ("Mobile Financial" OR "Mobile Payment" OR "Mobile wallets" OR "M-Payment" OR "M-Banking" OR "Mobile Banking" OR "Mobile" OR "m-money" OR "mobile money") AND ("technology acceptance model" OR "TAM"). Following the inclusion criteria, the time span for the search was set to include articles published between 2011 and 2021. By employing the specified keywords and time span, a total of 217 articles were obtained. Of those, 8 articles were found as duplicates; hence, they were removed. Therefore, the total number of remaining papers becomes 209.

The rest of the research articles underwent quality screening based on the most recent journals' rankings of the ABDC (Australian Business Deans Council) and the ABS (Association of Business Schools). The study retained only articles published in journals ranked (1) as A*, A, and B (therefore, excluding C and D ranked journals) regarding the 2022 ABDC journals' ranking or (2) as 4*, 4, 3, and 2 regarding the latest 2021 ABS ranking. Furthermore, the search and refinement phases were carried out in line with the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) (Moher et al., 2009). Each article's inclusion and exclusion criteria were applied to confirm its

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importance to the research questions. Hence, 24 studies were found to meet the inclusion criteria, so these articles were included in the final data analysis stage.

3.2.3 Data Coding and Analysis

In line with the research questions of this study, several attributes were coded and analyzed. These attributes include (1) external factors to TAM, (2) analytical research methods (mixed methods, amongst others.), (3) publication year, (4) active participative countries, and (5) the sample size of participants.

3.3 Results and Discussion

The research questions of this study were addressed under the following subsections:

3.3.1 Progress of Technology Acceptance Model Studies in MFS Adoption

Table 3-2 analyzes the external factors impacting the adoption of mobile financial services. Over the 24 analyzed research papers, 23 external factors were determined. It is essential to mention that merely the factors that appeared at least twice in the analyzed studies were accounted for in the review. Contrary to the earlier systematic review, which considered the core factors of the theoretical models in the analysis process (Ahmad, 2018), the current systematic review only considered the external factors to the original constructs of TAM, such as perceived usefulness, perceived ease of use, attitude towards use, behavioral intention, and actual use.

It can be seen that perceived security and compatibility are the most frequent factors affecting mobile financial services adoption, which appeared in seven studies. This is followed by subjective norm with six studies, Trust with five studies, facilitating condition, self-efficacy, perceived mobility, and perceived risk with four studies each, and external influence, innovativeness, and perceived mobility with three studies each. The rest of the depicted factors appeared in two studies only. These results support previous TAM-based mobile banking studies (Shareef et al., 2018), in which perceived security was a strong direct predictor of mobile banking adoption services through the lenses of TAM. Moreover, security and compatibility are some of the most important factors of mobile payment services (Di Pietro et al., 2015). An earlier study has also found that the strongest predictor of perceived usefulness appears to be perceived compatibility in mobile payment acceptance (Francisco Liébana-Cabanillas, Marinkovic, et al., 2018).

Table 3-2 Factors analysis

MFS Factors with TAM	Freq.	*MFS Factors with TAM*	*Freq.*	MFS Factors with TAM	Freq.
Perceived Security	7	*Perceived Mobility*	*4*	Perceived Credibility	2
Compatibility	7	*Risk*	*4*	Hedonic Performance Expectancy	1
Subjective Norm	6	*External Influence*	*3*	Utilitarian Performance Expectancy	1
Trust	5	*Innovativeness*	*3*	Technology Anxiety	1
Facilitating Condition	4	*Perceived Cost*	*2*	Satisfaction	1
Self-Efficacy	4	*Social Influence*	*2*		

N.B. Detail on each paper's reference used in **Table 3-2** is found in the author's published paper related to Chapter 3

Source: own elaboration

Concerning the security and the perceived risk, these results suggest that users, especially from developing states, will be more cautious as they are more used to performing their monetary transactions face to face, based on the rationale that banking transactions generally comprise monetary transactions. Therefore, the advancement of the security systems like eyes, voice, or fingerprint recognition can be used for mobile

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banking to create a secure user environment. Regarding compatibility factors, the results suggest that potential customers who feel mobile financial services are compatible with their needs, values, and previous experience will be highly willing to use the service (see **Table 3-2** above).

3.3.2 Distribution of Articles by Methods of Analysis

The bulk of studies (21 articles or 75%) on mobile financial services used structural equation modeling (SEM), partial-least square (PLS), and path analysis as the main tools of analysis (see **Table 3-3**). For the last two decades, SEM has become the most frequently adopted technique for many scholars assessing complex relationships between latent constructs (Astrachan et al., 2014). However, with the increasingly challenging requirements of covariance-based SEM (CB-SEM) regarding the distribution assumptions, sample size, and model complexity (Astrachan et al., 2014) (Joseph F. Hair et al., 2014), the use of the partial least squares SEM (PLS-SEM), a less restrictive method, is receiving widespread popularity and success with scholars (Souiden et al., 2019). PLS-SEM applications have grown exponentially in the past decade (Leguina, 2015), especially in the social sciences (e.g., (Ali et al., 2018) (Ringle et al., 2020)), and its use is expanding in marketing (Kumar et al., 2020) (Buzeta et al., 2020) (Gbongli et al., 2019) and information system research (Wynne Chin et al., 2020). Artificial neural network (ANN) analyses were conducted in three studies. Regression analysis, factor analysis, importance-performance map analysis (IPMA), and ANOVA were used in one study only. None of the studies were found using the qualitative approach.

Table 3-3 Primary method of analysis

Main method of analysis	Frequency	Reference
SEM, PLS, Path analysis	21	(Alhassan et al., 2020), (Khalilzadeh et al., 2017), (Sujeet Kumar Sharma, 2019), (A. A. Bailey et al., 2017), (Suhartanto et al., 2019), (Yen & Wu, 2016), (Giovanis et al., 2019), (Baabdullah et al., 2019), (Hussain et al., 2019), (Rafdinal & Senalasari, 2021), (Purohit & Arora, 2021), (Francisco Liébana-Cabanillas et al., 2014b), (Alalwan et al., 2016), (Al Khasawneh, 2015), (J. Zhang & Mao, 2020), (Francisco Liébana-Cabanillas, Marinkovic, et al., 2018), (Francisco Liébana-Cabanillas et al., 2015), (Di Pietro et al., 2015), (Goh & Sun, 2014), (Giovanis et al., 2021), (Su et al., 2018)
ANN	3	(Sujeet Kumar Sharma, 2019), (Giovanis et al., 2021), (Francisco Liébana-Cabanillas, Marinkovic, et al., 2018)
Regression analysis	1	(Changchit et al., 2017)
Factor analysis	1	(Changchit et al., 2020)
Importance-Performance Map Analysis (IPMA)	1	(Chawla & Joshi, 2021)
ANOVA	1	(Chawla & Joshi, 2021)

Source: own elaboration

3.3.3 Country/Region Analysis

This review also determined each assessed study's origin country, or region. **Table 3-4** shows that most publications were conducted in the USA (N = 5), with 20% of the analyzed studies. Spain recorded 12% (N = 3) of the entire analyzed studies. The rest of the statistics related to country and region are illustrated in **Table 3-4**. These results contradict those noticed in related mobile financial service studies, particularly the studies on mobile payment (De Albuquerque et al., 2016), which indicated that Kenya was the most frequent nation in conducting related studies. This contradiction in the studies can be explained by the differences in the inclusion and exclusion criteria of the selected studies, which might also play a critical role. Equally, it can be ascribed to the differences in the underlying theoretical models of the selected studies.

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Table 3-4 Top countries by publication frequency

Countries	Frequency	References
USA	5	(Khalilzadeh et al., 2017), (A. A. Bailey et al., 2017), (Changchit et al., 2020), (Changchit et al., 2017), (J. Zhang & Mao, 2020)
Spain	3	(Francisco Liébana-Cabanillas et al., 2014b), (Francisco Liébana-Cabanillas, Marinkovic, et al., 2018), (Francisco Liébana-Cabanillas et al., 2015)
Indonesia	2	(Suhartanto et al., 2019), (Rafdinal & Senalasari, 2021)
India	2	(Chawla & Joshi, 2021), (Purohit & Arora, 2021)
Greece	2	(Giovanis et al., 2021), (Giovanis et al., 2019)
Jordan	2	(Alalwan et al., 2016), (Al Khasawneh, 2015)
Africa	1	(Alhassan et al., 2020)
Oman	1	(Sujeet Kumar Sharma, 2019)
Taiwan	1	(Yen & Wu, 2016)
Malaysia	1	(Goh & Sun, 2014)
Saudi Arabia	1	(Baabdullah et al., 2019)
Bangladesh	1	(Hussain et al., 2019)
Thailand	1	(Changchit et al., 2020)
China	1	(Su et al., 2018)
Italy	1	(Di Pietro et al., 2015)

Source: own elaboration

3.3.4 Progress of Technology Acceptance Model Studies in MFS

The analyzed studies in the inspected period were categorized according to the year of publication, as presented in **Figure 3-1**. The studies are reflected through more or less constant frequency in the last eight years (2014-2018). The studies on mobile financial services did not show any articles using TAM from 2011 to 2013. This seems understandable as articles on new topics often face various challenges in publishing in the first years. It is essential to mention that we are dealing with articles that used only TAM with MFS as the study's model. Expectedly, the trend of publications on MFS has been slightly increasing and constant during the subsequent years to reach four publications per year throughout the last three years (2019, 2020, and 2021), which can potentially minimize the gap in the technology acceptance literature, especially with the ongoing boom in information technologies.

Figure 3-1 Frequency of studies per year.

Source: own research result

3.3.5 Distribution by Sample Size and Research Methods

The identification of sample size is an essential task for empirical research studies. Insufficient and inappropriate sample sizes can impact the accuracy and quality of research studies (Pradel et al., 2003). Accordingly, this review study categorized the

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selected papers based on the sample size used in each article. **Table 3-5** reveals the distribution of the analyzed articles according to the sample size used. It is noticed that 33.33% of the analyzed articles relied on a sample size between 301 and 400 in conducting the empirical studies. This is followed by 201 to 300 with 20.83%, 101 to 200, 401 to 500, and901 to 1000 together with 12.5%. There was also a sample size between 701 and 800, and above 2000that yields 4.16%. However, no publications were found between the ranges of 501 to 900. It can also be noticed that the number of larger sample sizes is relatively small compared with the number of small ones. Building upon small sample sizes might affect the generalization of results to the entire population.

Table 3-5 Distribution by sample size

Sample range	Number of studies	%
301 - 400	8	33.33%
201 - 300	5	20.83%
101 - 200	3	12.5%
401 - 500	3	12.5%
901 - 1000	3	12.5%
701 - 800	1	4.16%
Above 2000	1	4.16%
501 - 600	N/A	N/A
601 - 700	N/A	N/A
801 - 900	N/A	N/A

Note: N/A (Not Available).

Source: own research result

Table 3-6 shows that the selected articles were assessed based on the research methods employed. It can be seen that 95.83% of the analyzed articles (N = 23) have primarily relied on questionnaire surveys for collecting empirical data. Of the 23 studies, 19 (i.e., 82.61%) adopted convenient sampling techniques for the survey data collection, and the remaining 4 (17.39%) relied on the quota sampling technique. These results patronize the results observed in earlier mobile financial services-related systematic reviews (De Albuquerque et al., 2016) (Abdullah & Naved Khan, 2021), which stressed that questionnaire surveys were the most extensive techniques for collecting data. The dominant employment of questionnaire surveys for data collection is attributed to two significant reasons. First, questionnaire surveys can effectively and quantitatively analyze the respondents' intentions (Al-Emran et al., 2019). Second, these tools can appropriately ascertain the correlations among the constructs in the theoretical model (M. K. Malhotra & Grover, 1998).

Table 3-6 Detail on research methods, sample size adopted in MFS studies

Authors	Country/region, Sampling method (SM), Sample size
(Alhassan et al., 2020)	Region: Africa; SM: Syst. S. ; Size: 480
(Khalilzadeh et al., 2017)	Country: USA; SM: Quota sample (QS); Size: 412
(Sujeet Kumar Sharma, 2019)	Country: Oman; SM: CS; Size:225
(A. A. Bailey et al., 2017)	Country: USA; SM: CS; Size: 240
(Suhartanto et al., 2019)	Country: Indonesian; SM:CS; Size: 300
(Chawla & Joshi, 2021)	Country: India; SM: CS; Size: 744
(Yen & Wu, 2016)	Country: Taiwan; SM: CS; Size: 368
(Goh & Sun, 2014)	Country: Malaysia; SM: CS; Size: 105
(Giovanis et al., 2021)	Country: Greece; SM: CS; Size: 951
(Giovanis et al., 2019)	Country: Greece; SM: CS; Size: 931
(Baabdullah et al., 2019)	Country: Saudi Arabia; SM: CS; Size: 320
(Hussain et al., 2019)	Country: Bangladesh; SM: CS; Size: 247
(Rafdinal & Senalasari, 2021)	Country: Indonesia; SM: CS; Size: 400

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Continue to **Table 3-6** Detail on research methods, sample size adopted in MFS studies

Authors	Country/region, Sampling method (SM), Sample size
(Purohit & Arora, 2021)	Country: India; SM: CS; Size: 332
(Francisco Liébana-Cabanillas et al., 2014b)	Country: Spain; SM: QS; Size:2012
(Changchit et al., 2020)	Countries: USA, Thailand; SM: CS; Size: USA: 355; Size: Thailand: 400
(Alalwan et al., 2016)	Country: Jordan; SM: CS; Size: 343
(Al Khasawneh, 2015)	Country: Jordan; SM: CS; Size: 268
(Changchit et al., 2017)	Country: USA; SM: CS; Size: 309
(J. Zhang & Mao, 2020)	Country: USA; SM: QS; Size: 394
(Francisco Liébana-Cabanillas, Marinkovic, et al., 2018)	Country: Spain; SM: QS; Size: 191
(Francisco Liébana-Cabanillas et al., 2015)	Country: Spain; SM: CS; Size: 168
(Su et al., 2018)	Country: China; SM: CS; Size: 922
(Di Pietro et al., 2015)	Country: Italy; SM: CS; Size: 439

Note: Sampling method (SM); Convenience sample (CS); Systematic sampling (Sys. S); Quota sample (QS).
Source: own research result

3.4 Conclusion

3.4.1 Research Contributions and Implications for Future Research

This section provides the present systematic review's contributions and the implications it could yield for future attempts. First, identifying the most common factors affecting mobile financial services (MFS) adoption can support building a general model for elucidating MFS adoption regardless of context and subject. Further study could extend the TAM with the most common drivers (factors) identified in this study to build a comprehensive model for MFS adoption. Second, it has been observed that the number of TAM-based mobile financial services studies is slightly increasing yearly. Despite its development in 1989, these results increase the credibility of the TAM in mobile financial services fields and its future applicability across various empirical studies. In this vein, with the continuous effective use of TAM, further research could keep using the model in explaining the users' intentions toward any technology. Third, information technology corporations (system analysts and developers) and financial organizations can utilize the findings related to the influential factors as lessons learned. Therefore, this review can support improving the currently implemented solutions and consider enhancements in future technology to be more compatible, secure, and innovative. This can encourage end-users to gain the maximum benefits without fear of making mistakes. Fourth, several countries were identified according to their participation in TAM-based MFS studies. This result could assist scholars in conducting further empirical studies in the non-listed countries and assessing the antecedents of MFS adoption in such countries.

Fifth, it has been observed from the results that many of the analyzed studies were conducted with relatively small sample sizes. This might stem from the nature of the study and subjects and contexts in particular. In order to determine the required sample size in any empirical study, scholars might refer to two different sources. The first indicates the population size and the corresponding sample size to that population (Krejcie & Morgan, 1970). The second applied the G*Power tool by assessing the number of predictors in the theoretical model (Faul et al., 2009). Sixth, it has been perceived that most of the analyzed studies have relied on questionnaire surveys in conducting their empirical data. Further attempts can highlight mixed methods in collecting data, including surveys and interviews. Mixed methods can contribute better to the understanding of respondents' perceptions quantitatively and qualitatively.

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3.4.2 Limitations and Directions for Future Work

Although the study's results were quite exciting and played an essential role in providing an essential recapitulation of the TAM-based MFS studies, it also posits some limitations that need to be discussed. First, this study has concentrated on only a Scopus Database regarding the articles collection, which could lessen the amount of retrieved and analyzed articles. Future trials could emphasize retrieving articles from the Web of Science and Scopus to handle this limitation, as these two databases contain many research articles. Therefore, based on our results, we found thoughtful gaps in the extant literature and recommended future research directions.

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Chapter 4 Evaluation and Classification of Mobile Financial Services Sustainability using Structural Equation Modeling and Multiple Criteria Decision-Making Methods

4.1 Introduction

As a part of the shift of technology in the financial business, mobile financial services have been explored at an accelerated speed (C. L. Hsu et al., 2011). Innovations and technological expansion have emerged with significant advantages to the recent commercial market. Over the last few years, businesses have been redirecting their goals to making information system technology an essential part of their processes (Oliveira et al., 2014). Therefore, more and more literature is diverted to the IS-related field (R Agarwal & Prasad, 1999). The investigation of existing studies that recommend integrating various theoretical models to understand IT adoption has stressed that a comprehensive analysis in the context is required (Afshan et al., 2018; Oliveira et al., 2014). From these perspectives, an increasing number of researchers are focused on mobile financial services (MFS), considered the development of the information system (IS) domain (Abrahão et al., 2016; Al-Jabri & Sohail, 2012; Gbongli, Dumor, et al., 2016; Muñoz-Leiva et al., 2017).

MFS refers to any financial transaction remotely conducted by the application of a mobile phone (e.g., smartphone or tablet) and mobile software (e.g., apps programs) either through a banking service or network provider service (Gbongli, 2017; Yen & Wu, 2016). MFS providers allow their consumers the flexibility to access their financial services (access information inquiry, bill payment, and money transfers) anywhere and anytime via a mobile phone to support and improve service relationships by investing lots of resources using wireless internet technology (H.-F. Lin, 2011).

The studies of MFS that emphasized electronic money transfer include three major mobile technologies-related fields of study, primarily mobile banking services (MB), mobile payment services (MP), and mobile money transfer (MMT) services (Gbongli, 2017). MB remains part of the latest in a sequence of new mobile technological wonders (Mohammadi, 2015). Therefore, an expectation toward it should significantly impact the market (Safeena et al., 2012). Payment today has now progressed to mobile devices (m-devices) identified as mobile financial services, particularly mobile payments (Ooi & Tan, 2016). The emergence of mobile money is a significant innovation that has the potential to expand financial inclusion in developing countries in various ways, as noted by Gbongli et al. (2019). This technology provides access to financial services to many people whom traditional banks have ignored due to long travel distances and insufficient funds to meet the minimum deposit requirements for opening an account (Jack et al., 2013; Kikulwe et al., 2014). It benefits low-income populations in developing countries (J. Anderson, 2010), as it has several advantages (Assadi & Cudi, 2011) (Gbongli et al., 2019). In addition to the advantages granted to certain persons and companies, there are also advantages at the national economic level, primarily in emerging economies such as Hungary. The use of increasingly more accommodating tools may incentivize the suppressed use of cash, parallel to which the countability of economic performance with statistical instruments continues to improve; meanwhile, tax payment discipline also improves, and the total social cost of payments decreases, that is, overall the economy begins to whiten, leading to improved competitiveness (MNB, 2019).

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While tremendous benefits are associated with adopting MFS as opposed to traditional payment methods, such as physical exchange notes, cheques, and coins (J. Anderson, 2010), the adoption rate is far from full utilization in many developing countries. This is characteristically the situation of West African Countries and particularly Togo. Given the statistical information on the Statista Portal (2016), the smartphone population worldwide is predicted to be over five billion marks in 2019. Approximately 67% of the Togolese population subscribed to the mobile phone in 2015, while mobile internet users doubled between 2014 and 2015. However, the percentage rate of users of banking services is less than 15% (Couchoro, 2016), and the rate of consumer acceptance of mobile banking remains trivial (around 1%) when considering the expectation (Financial Afrik, 2015). It is, therefore, leading to deduct that mobile money services should fill this lacuna by providing significant input to increase the acceptance of MFS. This hope is far from being the case. The experiences of more developed countries also suggest that the same, not technological limitations were the primary obstacle to the extension of innovative payment solutions (Divéki et al., 2010). Therefore, the motives for the successful evolution or not together with the causes and motives for mobile money adoption, remain not understood sufficiently, which infers that the technology has not been extensively adopted. These trends reveal partial knowledge regarding the motivators and inhibitors that impact the acceptance of this mobile service (Hassan Hosseini et al., 2015).

Understanding why selecting MFS can help in strategy development and allow businesses to effectively communicate benefits to their customers (Johnson et al., 2018; Francisco Liébana-Cabanillas et al., 2014a). Mobile financial service operators might increase their attractiveness and competitiveness if they could enhance their strategies to satisfy the demand of their consumers. Therefore, understanding the various requirements of MFS users and the relative weight of each factor or criterion that could affect consumers' demand is necessary. One possible motive for a gap between these could be the perception of risk that limits consumers' capability to make informed decisions to partake in the benefit of MFS technology in Togo (Gbongli et al., 2017). This is particularly true for emerging nations, mainly in unstable countries where the consideration of the loss of privacy in the security system and the associated risk played a crucial part in adopting IT (Gbongli, Peng, et al., 2016). Moreover, studies in the past revealed that once there are risk issue concerns, the demand for trust becomes a necessity since trust and risk are interrelated facets (Gbongli et al., 2017; Mayer et al., 1995). Not only the developing countries facing the issue of e-business but also the reflection of the online risk has called for considerable attention amongst developed countries like Hungary, particularly in 2014 when the case of fraud risk in electronic payment transactions ascended in Hungary (the case was discussed in the work of Kovács & David in detail (Kovács & David, 2016)).

Driven by studies towards the multiple scopes for risk and trust and the central research on trust in contrast to risk from a novel information technology perspective (David Gefen et al., 2008), we suppose that initiating research into novel IT artifacts such as this research could enlighten how trust and perceived risk could influence the ultimate adoption of novel technologies in developing countries.

This study aims to disclose mechanisms related to behavior associated with MFS adoption and sustainable development when decision-making involves multiple criteria issues. One main research question is to understand how multi-dimensional trust and multi-faceted perceived risk perceptions affect a new emerging information technology such as MFS adoption at the individual level in an unstable country. Our approach differs

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from most prior studies that assess trust and risk perception of individual behavior. Indeed, most research investigating the acceptance and application of communicative IT has been done within stable, capitalist, and highly-developed communities. Moreover, most research undertakes that individuals have freedom of speech, the safety of their lives, essential protection, and business offered by the government. However, little has been known regarding the adoption of IT in emerging and dynamic societies (Goodman, 2011; Marett et al., 2015; Wells et al., 2010). Therefore, we explore the fundamental trust and risk allied with MFS technology usage in high poverty.

Most prior research typically tests trust as a single construct (Alsaad et al., 2017; Gao & Waechter, 2017; K. C. Lee & Chung, 2009) or investigates trust constructs and risk dimensions disjointedly (Johnson et al., 2018; Lowry, 2008). In other words, how to effectively assess trust and risk concerns concurrently remains a black box. Drawing on research in Information Technology (Luo et al., 2010; S. Park & Tussyadiah, 2017), we stress that multi-dimensional trust and perceived risk concepts may jointly play an integral part in individual behavior concerning adopting a novel MFS, and it is paramount importance for this to be investigated, particularly in developing countries such as Togo.

Furthermore, a plethora of research has been done to fully understand the factors affecting MFS adoption and its significance. However, most prior studies in this perspective have emphasized the general factors regarding adopting MFS, using explanatory statistical analysis as the research method (Aktepe et al., 2015) (Alzahrani et al., 2018). The beta coefficients gained in multiple regression techniques can be considered as the relative weights of the constructs. However, their values are obtained indirectly via the testing result. Additionally, a negative beta value can be found, making it quite complex to justify the importance of the resultant value (Shieh et al., 2014). Making decisions has continually been an important activity in day-to-day life. Therefore, using services such as MFS necessitates a careful decision from an individual so that he/she would not regret his/her decision ever since decision-making has emerged as a mathematical science today (Figueira et al., 2005). From there, multiple criteria decision-making (MCDM) techniques provide a crucial framework for companies to determine the most suitable strategy to meet the needs of their consumers, generate the necessary revenue, and thrive in a competitive environment (Valaskova et al., 2015).

In order to advance current IS research, Esearch & Koppius (2011) stressed that it is necessary to integrate decision modeling methods in IS research to generate data estimates and methods for assessing the analytical power of the result. Therefore, applying a combined analytic method stresses how integrating two or multiple data analysis techniques in either methodology or investigation can patronize confidence and validity in the resulting outcome (Gbongli et al., 2019; Scott & Walczak, 2009). Additionally, most managers make strategic decisions based on a single goal or dimension, but strategic planning is impacted by many different factors and is regarded from several perspectives (Y.-H. Hung et al., 2009). As the traditional notion of strategic planning lacks multidimensional prominence, this paper integrates the structural equation modeling and technique for order preference by similarity to the ideal solution (SEM-TOPSIS) method to construct the relationships between decision factors for MFS adoption while classifying the alternative of MFS. It is a unique decision-support technique grounded in structural modeling.

The primary objectives of this research are: To explore the influential antecedent of trust and risk perception at the multidimensional level regarding MFS adoption in Togo. To propose and validate model MFS acceptance using an SEM technique by employing

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data collected through experts of MFS and MFS experienced users. To develop an SEM-TOPSIS-based model for multi-criteria decision making by selecting the appropriate MFS type for MFS, grounded in experts' view, and by prioritizing the operative trust-risk factors while exposing the veiled relationship amongst factors that influence customers in the MFS. The present study has the following contributions:

Primarily, a growing number of recent studies link the multiple criteria decision-making (MCDM) techniques to financial decision-making (K. P. Gupta et al., 2017). In most cases, the traditional model of MCDM considers that the criteria (factors) are independently and hierarchically organized. Nevertheless, problems are often organized by interdependent criteria and dimensions and might even reveal feedback-like effects (Liou & Tzeng, 2012). TOPSIS is one of the most extensively adopted decision methodologies in technology, engineering, management, science, and business. TOPSIS approaches, as part of MCDM, improve the quality of decisions by generating more efficient, rational, and explicit development. However, previous works have not sufficiently kept pace. Thus, we believe there is a necessity for the methodical integration of SEM-TOPSIS to merge with a recent study performed in this field. This study incorporates a complex multi-criteria decision-making problem by assessing multidimensional trust and risk types in MFS that have rarely been investigated and touched on in past studies. As such, a literature review is conducted, and then SEM analysis is used to construct a hierarchical structure for trust and risk factors, including ten sub-factors. According to the identified criteria and sub-criteria and by considering relationships among them, TOPSIS is adopted for selecting the appropriate types of MFS, based on the critical factors that influence customers' trust and risk. Hence, the study contributes by proposing a solution that could effectively enhance trust and mitigation-perceived risk measures through a multi-level approach considered as a new added concept to planning strategy from the MFS perspective.

Secondly, one of the contributions of this study is to compare the outcomes of the TOPSIS and Analytical Hierarchical Process (AHP) techniques for a particular model to determine if there are significant differences. The previous work of Gbongli (2017) applied the SEM-AHP technique to evaluate the issues of risk and trust among a specific population, and the result of the AHP technique used in this study is based on that earlier work. As a result, this study shows that both approaches achieved comparable results were consistent, and generally agreed with each other. In other words, both methods classify mobile money services as the most important MFS used, followed by mobile payment as the second and mobile banking as the last. However, the TOPSIS method is better suited to the problem of MFS selection for this study area since AHP requires a long pairwise comparison process, and the consistency ratio requirement The paper provides a detailed methodology application that could be very useful insights for managers and researchers for their specific application.

The remainder of this paper is structured as follows. Section 4.2 offers a succinct overview of the literature and theory review. Section 4.3 presents the theoretical framework. In Section 4.4, the description of the research methodology and the procedure of this research are presented. Section 4.5 provides findings based on the research objectives. We conclude the work by discussing the findings, implications, limitations, and future study suggestions.

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4.2 Literature and Theory Review

4.2.1 Understanding Mobile Financial Services (MFS)

The rapid adoption of mobile devices in developing countries (Abu-Shanab & Abu-Baker, 2014), and widespread mobile financial services, have recently drawn practitioners' and academics' attention (Laukkanen, 2017). Since consumers are gradually spending more time online and are "going mobile," financial digitalization is now driving banks and network companies' providers to undertake the most extensive transition in their history. Mobile financial services (MFS) denotes the financial services and transactions performed using channels such as mobile devices (Hendricks & Chidiac, 2011).

MFS characterizes an area of innovation and strategic importance for global initiatives to counter poverty and mobile telecommunication providers (Nesse et al., 2018). It has been said to have carried about a positive shift in customers' perceptions in many countries. For the customer, MFS makes payments possible anytime, anywhere, and with the alleviated risk of theft (i.e., cash, particularly in underdeveloped communities) (Nesse et al., 2018). Mobile operators grasp MFS as an opportunity to engender revenue via an adjacent business (both basic payment and services) and recovery of cost and investments through enlarged consumer data usage (Dennehy & Sammon, 2015). The goals of MFS are accompanied by various advantages for banks, such as the decreased use of cash while cost-effectively serving the unbanked population and protecting current accounts and products. The primary benefit of MFS regarding trade involves higher Point-of-Sale (PoS) throughput, real-time messaging to users, and fewer costs for cash handling. Accessing transaction information and ownership of the user interface are further viewed as a critical perceived value of MFS.

These advantages could be equally valid for Togo. Not much attention has been given to empirical research on adopting MFS in Togo. Furthermore, in less affluent nations stricken with socio-political instability and vulnerability, MFS technologies may have different implications toward usage and are likely to impact the initial decisions to adopt (J. K. Lee & Rao, 2007; H. Li et al., 2011). The country of Togo sometimes encounters a kind of socio-political crisis. Based on the negative socio-political and external influences such as the physical atmosphere of development and growth, policies, regulations, and social environment unsupportive of adoption are suggested to hinder innovation adoption (Wisdom et al., 2014). MFS unavoidability might confront such challenges due to consumers' lack of trust in the novel wireless technology and their risk perceptions. We thus stress that users' trust and risk perception may impact their adoption of MFS services.

4.2.2 Theory and past research

As an emergent service, mobile financial services (MFS) have not been widely adopted by users. Therefore, scholars have paid attention to assessing the factors impacting user adoption. Furthermore, technology adoption is one main area of focus for information systems (IS) researchers. A diversity of theoretical perspectives has been developed to study MFS adoption. More assertively towards another direction, the current literature on consumer behavior related to acceptance of IT, such as MFS, tends to elaborate on a theoretical model of technology adoption theories (Safeena et al., 2013). They often employ the traditional information system models to explain user adoption of IT, like the theory of reasoned action (TRA), the motivational model, the diffusion of innovation theory (DOI), the technology acceptance model (TAM), innovation diffusion theory (IDT), theory of planned behavior (TPB), and unified theory of acceptance and use of

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technology (UTAUT). Numerous studies have employed these traditional frameworks to perform their research, and the rest integrated either previous models or added new variables to construct models to carry out their study. They examine whether the models' theoretical constructs are likely to affect the consumer acceptance of an MFS (Gbongli et al., 2019; E. L. Slade et al., 2013; Tam & Oliveira, 2017; Yan & Yang, 2015) or assess whether consumers are ready to adopt m-payments grounded in the supposed factors (E. Slade et al., 2015).

The TRA model stipulates that a particular behavior is directed by the individual's intention to conduct that action, which itself hinges on the attitude to behavior and subjective norms (Fishbein & Ajzen, 1975). For the TPB model, the perceived behavior was added to the attitude towards behavior and subjective norms that affect the intentions of people's perceived behavior and actual behavior (Icek Ajzen, 1985). Past studies elucidated behavioral perception control as the degree to which one has control over launching a particular behavior and facing the circumstances, while the complete volitional control over the behavior of interest is limited (Barua, 2013). Although their finding pinpointed the internal and external factors of perceived control, such as self-efficacy and facilitating condition, technology, and government sustenance, the utmost impact on the behavior is somehow associated with the type of innovation. As the extension to the TRA and TPB models, the TAM model bears a significance of perceived usefulness and perceived ease of use factor to affect actual behavior geared toward innovation (Davis et al., 1989). Based on the review of TAM literature, (Marangunić & Granić (2015) revealed seven past TAM-related studies. However, the goal of these works and the various analysis techniques adopted differ. For instance, (Legris et al. (2003) examine the question of whether the TAM explains actual use, while (Mortenson & Vidgen (2016) conducted a review of TAM studies employing the computational literature review (CLR). Moreover, TAM (Davis, 1989) and its extended version have been used in various online milieus to assess the adoption of consumers' online systems (Gbongli et al., 2019; David Gefen, Straub, Mack, et al., 2000).

The TRA model, however, has some drawbacks, comprising a significant threat of misleading attitudes and norms because attitudes can commonly be viewed as norms and conversely. Similarly, further explanatory variables are required for TRA (Thompson et al., 1991b; Webster & Martocchio, 1992). As such, TAM has been successfully combined with TRA and TPB in parsimonious capability (Suh & Han, 2003). The theory of adoption, such as DOI theory (Rogers, 2003), is a handy systemic background to define either adoption or non-adoption of new technology. The theory is that people will be more likely to accept innovation grounded in the facets and appearance of comparative benefit, compatibility, intricacy, trialability, and observability (Plouffe et al., 2001). Regardless of the enlightened strength of this model, the weaknesses go a long way in decreasing its power. For instance, the relationship between attitude and espousal or rejection of innovation was restricted (Lei da Chen et al., 2002; Karahanna et al., 1999); the innovation-decision process and the features of innovation remain unclear as well. The theory posits technology to pass via a linear stage; however, an intricate technology (Lyytinen & Damsgaard, 2001) has been perceived not on linear stages. Rendering to the critical review and meta-analysis of TAM (Legris et al., 2003), it was suggested as a useful model, although it suffers from the trade-off of dropping information richness resulting from the investigation (Napaporn, 2007).

Despite the various advantages that might be incorporated into every theory or model, their competency in predicting and elucidating is due to the degree to which the predictor

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could get a good proportion of variance explained in intention and usage behavior (Singleton et al., 1993; Taylor & Todd, 1995b). Even though the prevailing models are indicative of e-service or MFS acceptance behavior, many researchers believe that they are not sufficiently robust with regard to assessing all the aspects clients intend obviously throughout the various phases of their decision-making process and thus require further integration (El-Kasheir et al., 2009). After reviewing previous information acceptance models, George's findings revealed that trust consideration could be a major laudatory and backup for an online vendor (George, 2004).

It is important to recall that trust and risk are interrelated facets (Mayer et al., 1995), where the degree of importance of the situation depends on the impending outcome of risk. Given that the adoption of MFS becomes an important decision that consumers are required to make for a long-term impact, the function of risk is more likely to be vital. The extensive review of the literature revealed diverse antecedents to the adoption of mobile banking (Aboelmaged & Gebba, 2013; Narteh et al., 2017). Studies were carried out in both developing and developed countries; however, a limited number have been conducted in Togo (Afawubo et al., 2017; Gbongli, Dumor, et al., 2016). These outcomes are, therefore, insufficient to offer meaningful insights into predicting which multi-dimensional trust and risk influence customers' use of MFS in Togo while providing a strategy decision analysis framework for understanding the multiple factors that entail the decision of acceptance. Moreover, many of these theories and models were used in developed countries, and their direct application in developing countries such as Togo might not be sufficiently robust for the country's economic situation. Given that MFS belongs to information technology to which some adoption models might exist, it requires a distinctive conceptualization that might better pronounce the fact in emerging countries' situations.

Regarding these ends, this study uses trust and risk dimensionality literature components. It proposes conceptual research to envisage consumer appraisal of MFS (mobile banking, mobile payment, and mobile money transfer) adoption in Togo while ranking their perspective.

4.3 Theoretical Framework and Hypotheses

4.3.1 Antecedent of Trust

The concept of trust remains an intricate, multidimensional, and context-dependent paradigm (David Gefen & Straub, 2003). Past researchers emphasize the diverse aspects of trust, which frequently leads to discrepancies between numerous studies' outcomes. After the appeal from David Gefen et al. (2008) for additional new IT-related research on trust, there is a need to collectively assess the most crucial trust dimension, such as a disposition to trust, technology trust, and vendor trust that seems to impact MFS.

Some scholars have proposed trust dispositional, trust belief, and structural assurance (Mcknight & Chervany, 2001). From others' points of view, interpersonal trust, dispositional trust, and institutional trust are also essential constituents of the trust dimension (F. B. Tan & Sutherland, 2004). Others found the dimension of trust to be trusting behavior, dispositional to trust, and institution-based trust (Vidotto et al., 2012). Disposition to trust denotes the general susceptibility of a person to trust others (Nor & Pearson, 2008). It is grounded in the personality, which explains why some of us tend to either trust or mistrust and doubt others (Hallikainen & Laukkanen, 2018; Schoorman et al., 2007). Disposition to trust is, therefore, crucial for the establishment of initial trust and subsequently accommodating to less importance in the presence of pre-existed trust

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belief (David Gefen et al., 2003).

Technology Trust is considered an antecedent of trust. It connotes the readiness of an individual, or individual's technological dependency, to achieve a designated task by the positive feature incorporated in the technology (Mcknight et al., 2011), and the benefit arises from the particular technology (Muir & Moray, 1996). With this view, Technology Trust refers to the role of technology in building a trusting relationship with the user (Misiolek et al., 2002). From the above perspective, when an MFS user considers the technologies being applied to be reliable and consistent, the probability of assessing the aggregate service seems more promising, and trust will increase. Past research has revealed much importance and many benefits of technological trust in the behavioral field of application (Lankton et al., 2016; Mcknight et al., 2011; Meng et al., 2008; Min et al., 2008). Although admitting that the threefold technology aspect affects the environment of MFS (i.e., website, network, and mobile technology), the present study intends to treat them as a whole without separating them. As such, the user or potential user is called upon a strong level of comprehensive understanding purposively for MFS optimum usage.

Vendor Trust denotes the extent to which the consumer sees and believes that the vendor will accomplish the designated transactional requirements in risky or ambiguous conditions (B. P. Bailey et al., 2002). Many situations can raise consumers' trust in the vendor. An online consumer who perceives the vendor as presenting an opportunistic behavior can create a kind of reluctance within that particular consumer. Earlier studies have revealed a negative relationship between online vendors' opportunism and online consumers' trust (Paul A Pavlou et al., 2007). Trust, and in specific the confidence in the mobile vendor, plays a crucial role in the digital environment (Z. Liu et al., 2009; Nilashi et al., 2015; S. Yang, 2016; S. Yang et al., 2015). For Roger C. Mayer et al. (Rogers, 2003), vendor ability, integrity, and benevolence are crucial vendor trust features, although ability can also be regarded as vendor competence (Bhattacherjee, 2002). By relating that logic to the MFS environment, vendors with a good reputation/integrity will be less expected to bear unscrupulous behaviors and threaten their status. As a result, we posit the succeeding three assumptions to inspect the causal effect relationships between trust's antecedents and trust in the MFS perspective.

H1. The dispositional trust would significantly affect users' general trust in using MFS.

H2. The technological trust would significantly affect users' general trust in using MFS

H3. Vendor trust would significantly influence users' general trust in using MFS.

4.3.2 Antecedent of Perceived Risk

Perceived risk can denote a combination of uncertainty added to the severity of the consequence involved (Bauer, 1960). It is similarly taught as a kind of uncertainty and outcome (S. M. M. Cunningham, 1967). In the psychological field, perceived risk is the emotional sensitivity and subjective thoughts of various objective risks. Although it is the derivative of the objectives risk, nevertheless, they are different from each. From the perceptive of the trust-risk relationship, prior researchers understood that the readiness to take risks is a general characteristic of all trust circumstances (Costigan et al., 1998; Gbongli et al., 2017; Johnson-George & Swap, 1982). From this point, consumer trust could be noticed and subjected to the degree of the intricate risk presented in the situations (Koller, 1988). Awkwardly perhaps, due to the complex nature of trust and risk variables, countless scholars have disregarded the function of risk perceptions (D. Gefen et al., 2003). E-commerce trust investigators have shown that, when trust increases, the trustee's perception of risk reduces and impacts their attitudes toward the trustor, which successively influences the readiness for procurement (Jarvenpaa et al., 2000). In the view

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of the risk management field, risk is the construct associated with the cost of outcomes, empowering trust and risk as mirror images while both incorporate differing relationships (Grandison & Sloman, 2000). The study focuses on the rapport between trust and risk (D. Gefen et al., 2003), and trust-related works and empirical confirmation predominantly emphasize industrial relationships.

Nonetheless, theoretical and empirical support encountered in MFS is limited. When people trust others, they believe that those they trust will act as anticipated, which diminishes the intricacy of the interaction. Understanding the high convolution of the relationship between trust and risk concept, and considering likewise the absence of scholarly unanimity that lack on how to account their relationship via model (Johnston, Allen C. Warkentin, 2004), this study takes the view of a mediating relationship (D. Gefen et al., 2003) instead. On the mediating standpoint, if trust exists, then the risk perceived is reduced, which successively will impact the degree of decision-making to use MFS. Thus, higher trust in a technology would lower its perceived risk and consequently positively affect behavioral intention (Merhi et al., 2019).

These ideas of risk and others will endure a detrimental dominance on the acceptance of MFS. For instance, Swaminathan et al. (Swaminathan et al., 1999) revealed consumers' opposition to providing their credit card information through the Internet. With MFS, the consumers are required to entrust their credit card information and a complete account of information in most cases. Thoroughly, trust ameliorates the consumer's conception of online service and the related component, diminishing the level of the risk perception allied with the transaction process.

From the attribute of risk opinion, a plethora of researchers brought that studies on consumer risk perception are a kind of multi-facet concept (Featherman & Pavlou, 2003; Gbongli et al., 2017; Luo et al., 2010), which becomes the root of the aggregate perceived risk. To date, perceived risk has been employed to elucidate both offline and online risk shopping behavior. The finding derived from the work of Featherman & Pavlou (2003) on the consumer's adoption of e-services has been widely accepted, which classified perceived risk dimensions as economic risk, social risk, time risk, functional risk, psychological risk, and privacy risk. Bellman et al. (1999) informed regarding the prominence of time concerns and argued that it is a substantial predictor of online buying behavior. According to the finding, consumers who have less time are more likely to buy on the internet. The perception of time risk can refer to the integration of time lost and determination expended in acquiring any item or service (Murray & Schlacter, 1990). Grounded in this similar logic, the current study proposes that consumers are time-oriented and time-conscious and therefore value the potential time they might spend implementing, searching, and learning the application process of the new MFS.

Security/privacy risk is categorized as an intrinsic loss undeviatingly to fraud, scam, or hacktivists haggling the security of the user of an e-service (M.C. Lee, 2008). Security or privacy issues mostly arise when a customer transfers money from his/her account or deals with his/her secluded economic information, whereas others view this information without his/her consent (Littler & Melanthiou, 2006). The perception of costs applied to the MFS application reveals fear among consumers. Empirical evidence stresses that mobile banking acceptance is highly sustained by economic aspects such as beneficial fees regarding transaction service (A. S. Yang, 2009). Alternatively, it is impeded by economic considerations (issues centered on basic fees for assessing mobile banking), like cost burden (Cruz et al., 2010) or high payment incorporated in using mobile banking (H. Yao & Zhong, 2011). Therefore, the perception of cost risk tends to negate the

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adoption of mobile banking (Luarn & Lin, 2005).

Centered on the work of Featherman & Pavlou (2003) predominantly, and throughout the previous studies towards risk components, the present study deduces four important dimensions of perceived risk, which are expected to influence the consumer's overall risk concerning MFS adoption. They are perceived privacy, time, security, and financial risks in perceived cost. Hence, we can posit the following assumption based on the discussion being done in this section.

H4. Consumers' general trust would negatively relate to the perceived risk in MFS.

H5. Perceived privacy risk would significantly influence users' perception of the risk of using MFS

H6. Perception of time risk would significantly influence users' perceived risk of MFS

H7. Perception of security risk would significantly impact users' perceived risk of MFS

H8. Cost perceived would significantly influence users' aggregate perceived risk of using MFS

4.3. 3 Antecedents of MFS Adoption

Under this section, three antecedents (dispositional trust, trust, perceived risk) of MFS adoption will be taken into consideration. Being part of a personality trait, a disposition to trust can denote an individual's predilection to show reliance on humanity and to support a trusting standpoint concerning others (McKnight et al., 1998, 2002). Many researchers hypothesize that the disposition to trust as partaking positively impacts trust toward online shopping websites (McKnight et al., 2002). This relationship was also supported in various IS research, particularly in e-commerce (David Gefen, 2000; David Gefen & Straub, 2003; K. K. Kim & Prabhakar, 2004) and mobile banking (Guangming & Yuzhong, 2011). Accordingly, Gefen et al. (David Gefen et al., 2003) pointed out that disposition to trust is crucial, particularly for developing early trust, and befits less significant for established trust or pre-existing relationships trust beliefs. Once encountering people with trifling or no experience using the wireless internet as a platform for financial transactions, a disposition to trust is predictable to affect their trusting perception of the internet. People with a high disposition to trust are more likely to feel relaxed or secure when using wireless internet for financial transactions (Luo et al., 2010). Inferring from this lucidity to the MFS, we expect consumers with a higher disposition to trust to be more likely to espouse MFS than those with a lower disposition to trust.

The next antecedent of MFS adoption resides in risk perception. Since its application in consumer behavior literature (Bauer, 1960), the concept of perceived risk has been reviewed from multiple viewpoints. The classical decision concept considers risk perception as a function of the distribution of probable outcomes of conduct, its likelihoods, and subjective values (Pratt, 1964). Accordingly, risk encompasses two dimensions: uncertainty and outcome, where there is the possibility of experiencing a loss as a consequence of a behavior and the significance accredited to the loss (Cox, 1967; Kogan & Wallach, 1964). While various researchers have criticized this approach due to its strictness to apprehend a perceived risk variable equally ambiguous and indistinct (Sjoberg, 1980), some others were heightened to this concept definition as expected utility theory (Bonoma & Johnston, 1979; Currim & Sarin, 1983). Explicitly risk, therefore, carries on the subjectively driven expectancy of loss by the customer when denoting the perceived risk (L. F. Cunningham, Gerlach, Harper, et al., 2005). Internet banking and MFS, predominantly mobile banking, rely on a similar type of risk (M. S. Y. Lee et al., 2003), but only the information media channels differ. Prior IS studies showed that the

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imperative attitudinal of perceived risks impacts adoption behavior where much is based on the privacy risk and transaction security risk (Abrahão et al., 2016; K. K. Kim & Prabhakar, 2000; Laforet & Li, 2005; E. Lee et al., 2005; M. Tan & Teo, 2000). Preceding studies have equally supported the negative effect of the perceived risk of online usage and purchasing behavior (D. J. Kim et al., 2008; T.-P. Liang & Huang, 1998; Liao & Cheung, 2001; P.A. Pavlou, 2003). Likewise, earlier researchers agreed that the more risk is perceived by someone in purchasing context, the less probable he/she will be resolved to buy (Dowling & Staelin, 1994). Furthermore, the level of personal participation in the decision-making process exposes the degree of risk perceived combined with the significance attributed to the choice of the object while allowing for the individuals' desires, interest, and personal values (Assael, 1998; Coulter et al., 2003). Based on the perception of risk assigned in past works as the primary inhibitor elements of various IT fields, similarly, it is expected to affect the acceptance of MFS negatively.

Taking the antecedent of MFS from a different angle, the importance of trust has been revealed to be an extensive subject matter. Trust, combined with the previous definitions so far, denotes the readiness of one party to be exposed to the actions of another party dealing with the hope that the other will accomplish the designated task needed by the trustor (Mayer et al., 1995). The empirical findings of Jarvenpaa & Tractinsky (1999) revealed that trust influences purchasing decisions in various manifold cultures. The prominence of trust is so decisive that it may be extended to be viewed as the “wild wild west” of the 21st century (McKnight et al., 2002). The more MFS users or potential users believe and trust the services, the more they can develop an affirmative goal for its usage. User trust, which has been revealed to be an important adoption facilitator in many IS environments, lacks adequate inspection in the context of MFS as a whole. In line with the literature regarding the antecedent of MFS adoption in this study, we can, therefore, posit as follows:

H9. Disposition to trust will positively affect an individual's adoption of MFS.

H 10. User aggregate risk perceived would have a negative effect on the MFS adoption.

H11. User general trust will positively influence an individual’s adoption of MFS.

4.3.4 Conceptual Framework

We propose a research model to assess how trust and risk perceptions at the multidimensional level affect mobile financial services (MFS) acceptance in Togo. **Figure 4-1** summarizes the relationships described in the research hypotheses. The proposed model is used to identify several attributes as predictors of MFS. Based on the above discussion related to the suggested hypotheses, we considered three antecedents (dispositional trust, technology trust, and vendor trust) as a multi-dimensional trust for the general trust, four antecedents (privacy risk, time risk, security risk, and cost) regarded as a multi-facet perceived risk for the aggregate perceived risk. The remaining three antecedents (dispositional trust, perceived aggregate, and general trust) are used for consumers’ intention to adopt mobile financial services. Demographic variables entailing age and education levels are included in the model as control variables.

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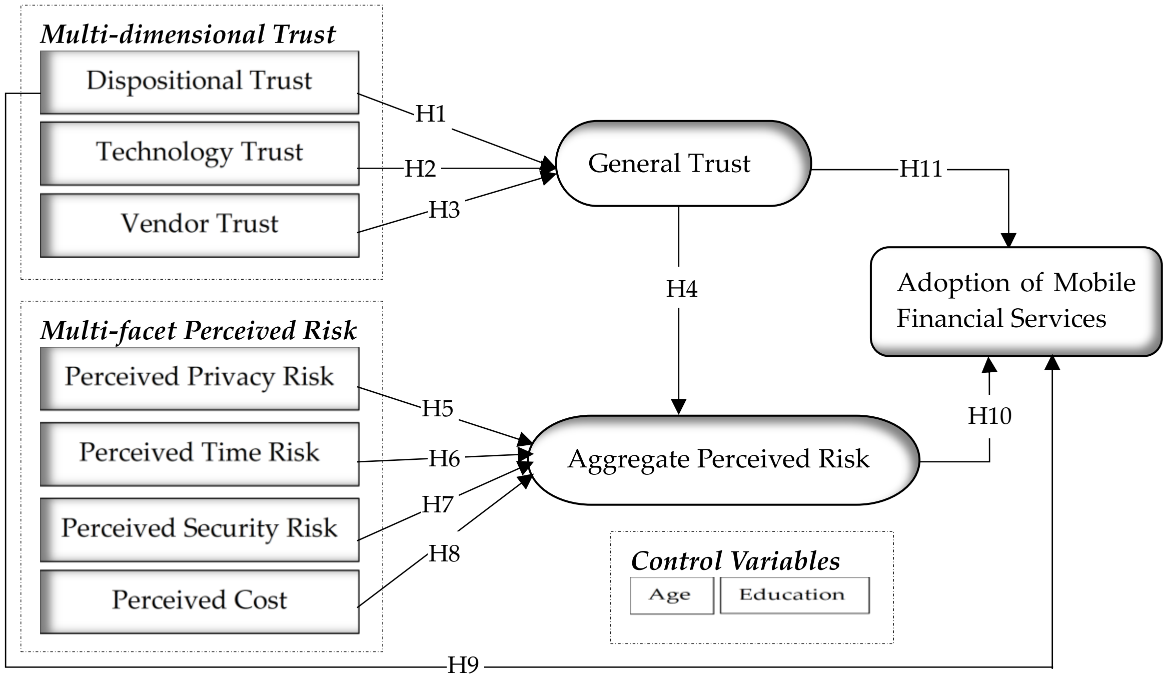

Figure 4-1 Proposed research model
Source: own elaboration

4.4 Research Methodology

4.4.1 Design and Data Collection

Various schools of thought questioned how data collected would be executed and the content of the studies. Amongst them, Cooper & Schindler (2003) have suggested two approaches to scrutinizing issues: One technique, called the observational approach, is to gather data on people, events, situations, and behavior, while the next one, the so-called communication approach, has considered the attitudes, expectations intentions, and motivator aspect.

As a result, this research used data collection via the communication approach, taking the form of a survey since the motive of the study turned out to capture the influential factor of MFS adoption once testing the research model. A survey instrument was then established for indicators and criteria development, which primarily got ratified after revising the constructs' suitability by the MFS experts. The preliminary draft of the questionnaire was prepared in English and then translated into French (the official language of Togo) for its assessment. Both questionnaires in English and French have been retained to avoid any confusion related to the scope, purpose, and content; so far, allowing the comparison of the versions for discrepancies issues and steadfastness to be easily acknowledged and established. Following the experts' advice and opinion, redundant and confusing items were either improved or removed. As a result, new items were included in the questionnaire, permitting the survey instrument's validity. The research model embodies ten factors; each factor remains evaluated with multiple items. Also, all items were accommodated from existing literature to increase content validity (Straub, DetmarBoudreau & Gefen, 2004). There were two types of questionnaires. The first type (SEM questionnaire) was divided into two parts. The first part was distributed with the bio-data of the sample, and the second part answered the MFS questions using

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the five-point Likert scale bounded from strongly disagree (1) to strongly agree (5). The final measurement scales, items, and their sources are listed in “Appendix A”.

For the second type of questionnaire (TOPSIS), we arbitrarily contacted users and potential users and questioned whether they had mobile MFS usage experience to ensure their familiarity to some extent, as recommended (Gbongli, 2016, 2017). Thus, those with two or more MFS experience years were further invited to fill out the TOPSIS questionnaire format.

The empirical study took almost three months of data collection due to the delay in obtaining some participants’ responses and the awkward time indicated by some. Data were collected at some of the busiest and most crowded places of the capital town Lomé (i.e., Assivito, Dekon, Be, and Université de Lomé), where potential users and currents users of mobile financial services (MFS) can relatively be found and inspected better than in other sectors. Literate people filled in their survey questionnaires themselves, whereas, for illiterates, help was given. The questionnaire took almost 10–15 minutes to complete by a given participant. The estimated accessible population of Lomé is 837,437 (N’Guissan, 2012). Therefore, the estimated adjusted sample size for this research should have a minimum of $399.8090 \cong 400$ (Yamane, 1967). In a situation involving minor participants, informed consent has been given by legal representatives and the minor participants 'assent' before partaking in a study. An exception to this procedure is when teenagers are employed and living independently.

Once the data collection procedure was completed, we examined all questionnaires and discarded cases with too many missing and/or rushed responses.

As such, 538 questionnaires, which fulfilled the minimum requirement, were both ready and yielded usable samples. Amongst them, 294(54.6%) were male and 244(45.4%) female. Seventy-five (13.9 %) respondents were aged below 18 years, 145(27%) aged between 19-24 years, 199 (37%) were aged between 25-30 years, and 119(22.1%) aged above 31 years. Regarding educational qualifications, the majority of respondents (two hundred and sixty-seven) had a high school certificate or below, i.e., Baccalaureate (49.6%), 203(37.7%) had a graduate degree, and 57(10.6%) had a master's degree. The remaining 11 (2%) had a doctorate. Concerning MFS years of experience, 187(34.8%) of respondents claimed to have no experience with MFS, 194(36.1%) used it for less than one year, 125(23.2%) MFS usage ranged from 1-2 years, 26(4.8%) were found between 3-4 years of MFS experience. Only 6(1.1%) had MFS experience over five years. Hence, very few respondents had MFS experience above three years from the deduction. Moreover, they are those respondents engaged in MFS application at the early stage of its implementation (Most MFS companies in Togo started launching their activities in 2013) and dwelled on it.

4.4.2 Proposed Technique of Data Analysis: SEM-TOPSIS Methods

The SEM-TOPSIS technique was employed to construct the MFS evaluation decision support system. Therefore, SEM was utilized to generate critical criteria and weights, whereas TOPSIS was used to engender the rank and score of alternatives and permitted the fullness of the data, improving the data accuracy via group decision-making.

SEM is suitable for estimating and testing casual relationships using statistical data and qualitative assumptions (Gbongli et al., 2019; Kumar Mittal & Singh Sangwan, 2014). It is a second-generation multivariate technique that tolerates the simultaneous assessment of multiple equations and embraces multiple regression analysis, factor analysis, and path model analysis (J. F. F. Hair et al., 2006). SEM incorporates the fundamental analysis of construct concurrently rather than separately (WW Chin, 1998),

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with this application being emergent in the social sciences (J. C. Anderson & Gerbing, 1988). Accordingly, it is the handiest method adapted for checking causative relations between predictors and adoption behavior (J. F. F. Hair et al., 2006; Schumacher & Lomax, 1996). It offers greater flexibility in matching a theoretical model with a data sample compared to techniques like PCA and factor analysis (Aloini et al., 2011).

TOPSIS: Technique for Order Preference by Similarity to Ideal Solution. The various process of TOPSIS will be explained in the analysis section.

4.5 Data Analysis

4.5.1 Measurement and Hypotheses Testing with SEM Analysis

We performed exploratory factor analysis (EFA) employing maximum likelihood estimation with Promax because of the large sample of data set (n=538) and its intricacy related to the outcome's elucidation, which is trivial in resolving the correlation. The EFA reveals the output of KMO as 0.809 and Bartlet's test of sphericity to be significant at α=0.000 with a Chi-square of 11598.920, indicating the relevance for performing exploratory factor analysis (Kaiser, 1974). Besides, the communalities for each variable were sufficiently high (the lowest was 0.343, the majority were beyond 0.597, and the greatest was 0.975), showing evidence that these variables were effectively correlated for factor analysis. The ten-factor model obtained a total variance explained with more than 60% and all extracted factors partaking in eigenvalue beyond 1.0.

To continue assessing our quantitative model, we settled the subsequent analysis in two phases (J. C. Anderson & Gerbing, 1988): first, via confirmatory factor analysis (CFA), we appraised both reliability and discriminant validity of the ten constructs (Campbell & Fiske, 1959). The outcomes will achieve validity unless the researchers employ constructs that diverge from another construct in a similar model (Campbell & Fiske, 1959). We valued the structural model from the second step and then SEM for hypotheses testing. These last two steps are adopted from previous studies (Gbongli et al., 2017; Zhou, 2012b). Hence, we estimated the reliability of each construct based on three indices, such as composite reliability (CR), average variance extracted (AVE), and Cronbach's alpha (CA). The suggested values for good measures were at least 0.70, 0.50, and 0.70, respectively (Fornell & Larcker, 1981) (see **Table 4-1**). In patronage of convergent validity, the AVE was higher than 0.5 for all constructs, and all item factor loadings remained beyond the minimum threshold of 0.4 (J F Hair et al., 2010).

Moreover, all loadings of items arose in the corresponding construct, and no item was loaded with a high value in another construct. This technique was espoused in past research (Gbongli et al., 2019; Y. Hwang, 2014; Zhou et al., 2010). As such, we established that our ten constructs displayed convergent validity (see **Table 4-1** below).

Table 4-1 Reliability and validity in CFA

	CR	AVE	MSV	MaxR (H)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1)	0.846	0.647	0.227	0.848	**0.804**									
(2)	0.933	0.779	0.133	0.965	0.108	**0.883**								
(3)	0.904	0.704	0.087	0.975	0.216	0.067	**0.839**							
(4)	0.860	0.609	0.057	0.979	0.168	0.157	0.155	**0.780**						
(5)	0.855	0.664	0.227	0.981	0.476	0.020	0.230	0.144	**0.815**					
(6)	0.843	0.577	0.056	0.984	0.236	0.061	0.114	0.011	0.235	**0.760**				
(7)	0.856	0.600	0.133	0.985	0.041	0.365	0.044	0.238	-0.022	-0.072	**0.775**			

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To continue to **Table 4-1** Reliability and validity in CFA

	CR	AVE	MSV	MaxR (H)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(8)	0.811	0.594	0.065	0.987	0.127	0.155	0.113	0.232	0.091	0.035	0.255	**0.771**		
(9)	0.798	0.571	0.013	0.987	0.102	0.098	0.065	-0.004	-0.035	0.086	0.075	0.115	**0.756**	
(10)	0.820	0.610	0.087	0.988	0.228	0.051	0.295	0.064	0.198	0.216	-0.042	0.019	0.104	**0.781**

Note: (1): DTrust-Dispositional Trust; (2): TTrust-Technological Trust; (3): Vtrust-Vendor Trust; (4): PPrivR-Perceived Privacy Risk; (5): PTimeR-Perceived Time Risk; (6): PSecurR-Perceived Security Risk; (7): PCost-Perceived Cost, (8): PRisk-Perceived Risk; (9): AdMFS-Adoption of MFS; (10) General Trust (G-trust).

Source: author's computation

We designed **Table 4-2** to portray the goodness of fit of CFA and SEM. Except for the goodness-of-fit index (GFI) for CFA, slightly below the recommended, as this index is sensible to sample size, we use a large sample size (n = 538); for all indexes, our measurement model and structural model indicated sufficient goodness of fit.

Table 4-2 Goodness of fit (CFA and SEM)

Indices	Abbreviation	CFA Value	SEM Value	Thresholds
Chi square	x^2	1068.904	30.445	Pval>0.05
Normed chi-square	$x^2_{/DF}$	2.104	1.903	1< x2/df< 3
Root mean square residual	RMS or RMR	0.066	0.015	<0.08
Goodness-of-fit index	GFI	0.889	0.991	>0.90
Adjusted GFI	AGFI	0.862	0.955	>0.80
Normed fit index	NFI	0.900	0.941	>0.90
Comparative fit index	CFI	0.944	0.968	>0.93
Tucker-Lewis index	TLI	0.935	0.869	0<TLI<1; TLI > 0.9
Root mean square error of approximation	RMSEA	0.045	0.041	<0.05 excellent fit <0.08 good fit

Source: author's computation

Before the structural model, we conducted a common method bias. Since the data for the variable was led through a single method (survey), we performed a test to check if a common factor might have impacted our outcomes. Hence, the test adopted was an unmeasured latent factor suggested by Podsakoff et al. (Podsakoff et al., 2003) and Siemsen et al. (Podsakoff et al., 2003) towards studies that do not measure a common factor, mentioned as a common latent factor (CLF) method. The most prevailing and best method in checking the CMB is the zero-constrained test, where the CLF is involved along with Marker if accessible (Podsakoff et al., 2003). This approach checks whether the shared variance across all variables differs significantly from zero. In case it is, then there are bias issues. To proceed, we computed the chi-square difference test among the unconstrained model and the model per all paths regarding the CLF constrained to be zero. Since the result is markedly different from zero, we can conclude that method bias does occur in our measures. Thus, moving to the causal model based on the result, CLF was retained for our structural model (by imputing composites in AMOS in the presence of CLF), which provided CMB-adjusted values.

We also check for invariance (configurable and metric) due to the presence of two groups, such as gender, in our data to see whether the factor and loading are adequately equivalent across groups. Davidov (2008) has claimed that assessing path coefficients could only be useful if the invariance test was done beforehand. The result signpost that the model fit of the unconstrained measurement models (per groups loaded distinctly) presented a sufficient fit ($\chi2$ /DF = 1.623, TLI=0.928, CFI=0.938, RMSEA=0.034) when assessing a freely estimated model across genders. Grounded on the result, the model is configurally invariant. Once the model was constrained to be equal, the result of the chi-

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square difference test revealed the p-value (0.226) to be nonsignificant. So, the measurement model satisfies the benchmark criteria for metric invariance across gender as well. Then and there, we move on to making the composite from this measurement model to build SEM for verification of hypotheses testing. The structured model's results and parameters were obtained while controlling for age and education. The standardized path coefficients, path significances, and explained variance $\boldsymbol{R^2}$ of the structural model (See **Figure 4-2**).

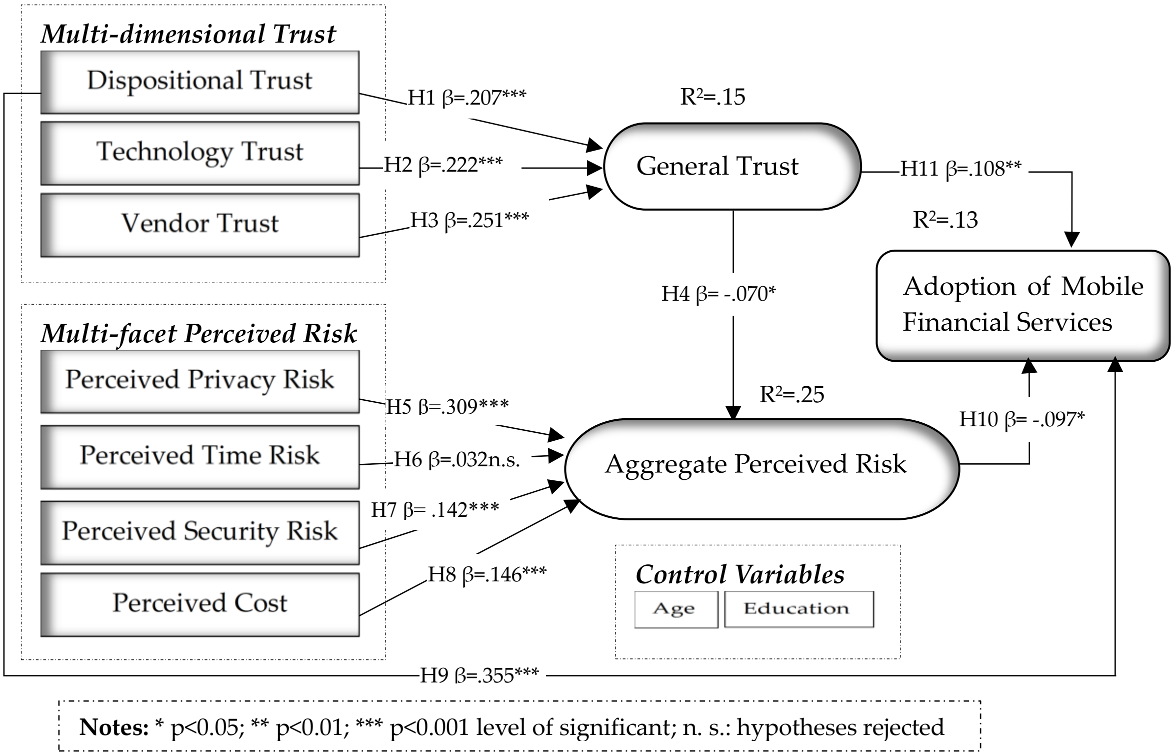

Figure 4-2 Final model after validation

Source: own research result

4.5.2 TOPSIS Analysis

The Technique for order preference by similarity to ideal solution (TOPSIS) is a multiple criteria decision-making (MCDM) technique developed by Hwang & Yoon (C.-L. Hwang & Yoon, 1981). It is grounded in the criteria that the alternative should have the shortest distance from the positive ideal solution and the farthest from the negative ideal solution (S. K. Patil & Kant, 2014). (Dhull & Narwal, 2018) (Gbongli, 2016) (Gbongli, Dumor, et al., 2016) (Mahdevari et al., 2014). Compared to other MCDM methods, TOPSIS necessitates limited subjective inputs from decision-makers (Vinodh et al., 2014) and remains a deterministic technique. It provides both positive and negative solutions, which is beneficial for applications with considerations such as cost and benefits, and it is a rational method that works agreeably across various application areas (Behzadian et al., 2012). Recall that the process of the SEM-TOPSIS can be characterized as follows. Primarily, SEM was applied to compute the hierarchical criteria and their relatives to ensure their significance. This is why the relative weightage obtained from SEM is reflected as more valid than any other method. The antecedent of trust and perceived risk given by the SEM model was deliberated for the relative weightage of the sub-criteria.

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The computation of TOPSIS methods grounded on C.-L. Hwang & Yoon (1981), C. T. Lin & Tsai (2010), and predominantly the one required for grouping decisions (Shih et al., 2007) were adopted and presented as follows:

Step 1: Construction of decision matrix $\mathrm{D}^{\mathrm{k}}, k = 1, \dots, K$ for each DM. The matrix structure can be viewed as follows:

$$\mathrm{D}^{\mathrm{k}} = \begin{array}{c} \\ \\ A_1 \\ A_2 \\ \vdots \\ A_{\mathrm{i}} \\ \vdots \\ A_{\mathrm{m}} \end{array} \begin{array}{c} n\ Criteria \\ \begin{array}{cccccc} X_1 & X_2 & \cdots & X_{\mathrm{J}} & \cdots & X_{\mathrm{n}} \end{array} \\ \begin{bmatrix} \mathrm{x}_{11}^{\mathrm{k}} & \mathrm{x}_{12}^{\mathrm{k}} & \dots & \mathrm{x}_{1\mathrm{j}}^{\mathrm{k}} & \dots & \mathrm{x}_{1\mathrm{n}}^{\mathrm{k}} \\ \mathrm{x}_{21}^{\mathrm{k}} & \mathrm{x}_{22}^{\mathrm{k}} & \dots & \mathrm{x}_{2\mathrm{j}}^{\mathrm{k}} & \dots & \mathrm{x}_{2\mathrm{n}}^{\mathrm{k}} \\ \vdots & \vdots & \dots & \vdots & \dots & \vdots \\ \mathrm{x}_{\mathrm{i}1}^{\mathrm{k}} & \mathrm{x}_{\mathrm{i}2}^{\mathrm{k}} & \dots & \mathrm{x}_{\mathrm{ij}}^{\mathrm{k}} & \dots & \mathrm{x}_{\mathrm{in}}^{\mathrm{k}} \\ \vdots & \vdots & \dots & \vdots & \dots & \vdots \\ \mathrm{x}_{\mathrm{m}1}^{\mathrm{k}} & \mathrm{x}_{\mathrm{m}2}^{\mathrm{k}} & \dots & \mathrm{x}_{\mathrm{mj}}^{\mathrm{k}} & \dots & \mathrm{x}_{\mathrm{mn}}^{\mathrm{k}} \end{bmatrix} \end{array} \tag{1}$$

Where A_i refers to the likely alternatives of the decision process i with $i = 1, \dots, m$; X_j denoting the attribute or criterion $j, j = 1, \dots, n$; with both quantitative and qualitative data. The value $\mathrm{x}_{\mathrm{ij}}^{\mathrm{k}}$ remains, therefore, the performance score of alternative A_i in relation to attribute X_j by decision-maker $k, k = 1, \dots, K$, while x_{ij}^k is the element of D^{k}. It is important to mention that there should be K decision-maker matrices designed for K participants of the group. Moreover, the output of the qualitative attribute from each alternative can also be intentionally set as discrete values or linguistic values (referring to **Table 4-4**) so that the quantitative values can be set in the decision matrix above.

Step 2: the normalized decision matrix $\mathrm{R}^{k}, k = 1, \dots, K$ is generated for each DM. Vis-à-vis to any $DM\ k$, the vector normalization technique is used for computing the element r_{ij}^k from the decision matrix R^{k} which can take any linear-scale transformation to preserve $0 \leq r_{ij}^k \leq 1$ inequality. Since we consider the vector normalization operation, then r_{ij}^k is given as:

$$r_{ij}^k = \frac{x_{ij}^k}{\sqrt{\sum_{\mathrm{j}=1}^{\mathrm{n}} \left(\mathrm{x}_{\mathrm{ij}}^{\mathrm{k}}\right)^2}}, \tag{2}$$

Where $i = 1,2, \dots, m$; $j = 1,2, \dots, n$; and $k = 1,2, \dots, K$. It is also necessary to clue that the vector normalization method makes provision as to which one represents a cost criterion for additional management. Moreover, there is no need to directly assess the weighted normalized as per the case of the original TOPSIS (Shipley et al., 1991).

Step 3. The positive ideal solution V^{k+} (PIS), is made of all the best performance scores and the negative-ideal solution V^{k-} (NIS) is made of all the worst performance scores at the measures in the weighted normalized decision matrix for each DM $k = 1, \dots, K$. For any given $DM\ k$, his/her PIS and NIS can be characterized in the form of

$$\mathrm{PIS} = \mathrm{V}^{\mathrm{k}+} = \{\mathrm{r}_1^{\mathrm{k}+}, \dots \dots, \mathrm{r}_{\mathrm{n}}^{\mathrm{k}+}\} = \left\{ \left(\max_i \overset{k}{\underset{ij}{r}} \middle| \mathrm{j} \in \mathrm{J} \right), \left(\min_i \overset{k}{\underset{ij}{r}} \middle| \mathrm{j} \in \mathrm{J}' \right) \right\} \tag{3}$$

$$\mathrm{NIS} = \mathrm{V}^{\mathrm{k}-} = \{\mathrm{r}_1^{\mathrm{k}-}, \dots \dots, \mathrm{r}_{\mathrm{n}}^{\mathrm{k}-}\} = \left\{ \left(\min_i \overset{k}{\underset{ij}{r}} \middle| \mathrm{j} \in \mathrm{J} \right), \left(\max_i \overset{k}{\underset{ij}{r}} \middle| \mathrm{j} \in \mathrm{J}' \right) \right\} \tag{4}$$

Where J is related to the benefit criteria and J' allied with the cost criteria, $i = 1, \dots, m$;

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$j = 1, \dots, n$; and $k = 1, \dots, K$

Step 4. A weigh vector W is allocated to the attribute set for the group. Each DM will produce weights for attributes as w_j^k where $j = 1, \dots, n$ and $\sum_{j=1}^{n} w_j^k = 1$; and for each DM $k = 1, \dots, K$. Each element of the weigh vector W will result from the operation of the corresponding components of the attributes' weights for every DM.

Step 5. Evaluate the separation measure through the positive ideal and the negative ideal solutions, $\overline{S_I^+}$ and $\overline{S_I^-}$, relatively to the group. Due to the group decision concerning this research, this step requires two sub-steps, where the initial one considers the distance measure for individuals while the next one aggregates the measure for the group.

Step 5a. Assessment of the measure from PIS and NIS individually: The n-dimensional Euclidean distance can compute the distance of an alternative j to the ideal solution. Separation of each alternative from the positive ideal solution $\mathrm{S_i^{k+}}$ is then provided by equation (5) below:

$$\mathrm{S_i^{k+}} = \sqrt{\sum_{j=1}^{n} w_j^k \left(v_{ij}^k - v_j^{k+}\right)^2} \text{, for alternative } i, i = 1, \dots, m \tag{5}$$

Similarly, separation from the negative ideal solution $\mathrm{S_i^{k-}}$ is then given by

$$\mathrm{S_i^{k-}} = \sqrt{\sum_{j=1}^{n} w_j^k \left(v_{ij}^k - v_j^{k-}\right)^2} \text{, for alternative } i, i = 1, \dots, m. \tag{6}$$

- Step 5b. Assessment of the measure from PIS and NIS for the group. In this part, the individual group measure of each alternative is to be integrated via an operation $\otimes$ for all DMs, $k = 1, \dots, K$. As such, the twofold measure of the PIS and NIS are presented below

$$\overline{S_i^+} = \overline{S_i^{1+}} \otimes \cdots \otimes \overline{S_i^{K+}} \text{, for alternative } i, \tag{7}$$

$$\overline{S_i^-} = \overline{S_i^{1-}} \otimes \cdots \otimes \overline{S_i^{K-}} \text{, for alternative } i \tag{8}$$

Though this operation can provide various choices like geometric and arithmetic mean with their related extended, this study pondered only the geometric one for the group computation. Its calculation's formulae are shown for PIS and NIS (Eq. 9); (Eq. 10)

$$\overline{S_i^+} = \left(\prod_{k=1}^{K} S_i^{k+}\right)^{\frac{1}{K}} \text{, for alternative } i, \tag{9}$$

$$\overline{S_i^-} = \left(\prod_{k=1}^{K} S_i^{k-}\right)^{\frac{1}{K}} \text{, for alternative } i. \tag{10}$$

Where $i = 1, \dots, m$; $k = 1, \dots, K$

Step 6: The ranking score $\overline{C_i^*}$ is computed as

$$\overline{C_I^*} = \frac{\overline{S_i^-}}{S_i^+ + S_i^-}, i = 1, \dots, m \tag{11}$$

With $0 \leq \overline{C_I^*} \leq 1$. When C_I^* is closed to 1, the alternative is considered ideal; and when C_I^* is closed to 0, the alternative is considered non-ideal. The higher the index values, the higher the rank order, so the better the alternative's performance.

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4.5.3 Case Study using Combined SEM-TOPSIS Techniques

In this paper, a case study is conducted to demonstrate the feasibility of the proposed methodology (SEM-TOPSIS). The study examines data provided by 74 experienced users and experts of mobile financial services regarding the MFS classification with a particular focus on applying the TOPSIS technique. The relative weightage is computed from the standardized total effect, normalized obtained from the SEM technique (Gbongli, 2017; Punniyamoorty et al., 2012), and presented in **Table 4-3**. The weightings showed the importance of each sub-criteria for the MFS companies.

Table 4-3 Relative weightage of sub-criteria

DTrust	TTrust	VTrust	PPrivR	PTimeR	PSecurR	PCost
0.265	0.128	0.177	0.200	0.021	0.109	0.101

Note: (1): DTrust-Dispositional Trust; (2): TTrust-Technological Trust; (3): Vtrust-Vendor Trust; (4): PPrivR-Perceived Privacy Risk; (5): PTimeR-Perceived Time Risk; (6): PSecurR-Perceived Security Risk; (7): PCost-Perceived Cost.

Source: own research result

To determine the relative importance of MFS alternatives for each sub-criteria in relation to the criteria of Trust and Risk, a decision matrix for evaluating alternative performance (Eq.1 step 1) was constructed. Participants were requested to assign values ranging from one to nine for the sub-criteria, as shown in **Table 4-2**.

Table 4-4 Transformation of linguistic scale into quantitative values

Linguistic Scale	Quantitative Values	
	Benefit-Max	Cost-Min
Very High	9	1
High	7	3
Average	5	5
Low	3	7
Very Low	1	9
Intermediate values between the two-adjacent judgment: (2,4,6,8)		

Source: own research result

Following the procedure of the TOPSIS method, through a TOPSIS algorithm built-in MATLAB technical computing tool, the relative weightage of MFS allied with each sub-criterion is calculated and shown in **Table 4-5**. After aggregating the individual PIS and NIS via geometric mean from Step 5b eq. (7) and eq. (8), then the final score $\overline{\boldsymbol{C}_{\boldsymbol{I}}^{*}}$ is computed using Eq. (11) of Step 6, followed by ranking the MFS alternatives as portrayed in **Figure 4-3** and **Table 4-6**.

Table 4-5 Summary of the relative weightage of MFS to each sub-criterion

Relative weightage of MFS to each sub-criterion							
Sub-criteria weightage	0.265	0.128	0.177	0.200	0.021	0.109	0.101
Sub-criteria	DTrust	TTrust	VTrust	PPrivR	PTimeR	PSecurR	PCost
MB	5.40	4.78	6.23	-3.56	-7.53	-4.20	-6.50
MP	8.50	5.40	4.43	-2.34	-8.20	-5.00	-7.00
MMT	7.30	4.70	5.11	-1.42	-8.00	-4.48	-7.20

Source: own research result

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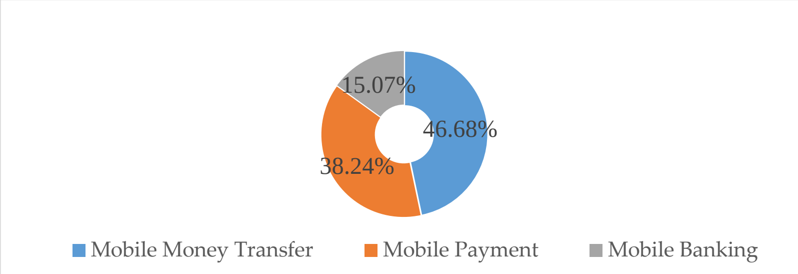

Figure 4-3 Classification of MFS alternatives using TOPSIS (% representation)
Source: own research result

Table 4-6 Results of 3 alternatives of MFS ranking using TOPSIS

MFS	$\overline{C_I^*}$	Rank	% distribution of coefficient
MMT	0.7454	1	46.68%
MP	0.6106	2	38.24%
MB	0.2407	3	15.07%

Source: own research result

4.6 Discussion

New technology adoptions are impacted mainly by many factors, which may vary from technology concerns to the trust dimension, the perception of risk facets, and the behavior of users, to mention a few. The intricacy and significance related to the effort in elucidating the motives or reasons for users' adoption or rejection of new IT have led to the development of various concepts. Furthermore, there are many studies on the influence of trust and perceived risk with their determinant towards the adoption decision in an online environment.

Conversely to prior research works, this study scrutinizes the influence of critical variables such as multi-dimensional trust and perceived risk facets on the consumers' adoption behavior of MFS. It incorporates each of them into the MFS alternative decision-making scenario. Some postulations were made towards the possible relationship among the factors. The findings are yet to be probed purposively to draw an important conclusion and implication. The MFS structural model analysis result, regarded as a final model after validation, is summarized and portrayed in **Figure 4-2**. Specifically, the discussion section is scheduled to be under two sections. The first section will be made with SEM methodology grounded on hypotheses results, which are three sets. The first set: includes hypotheses associated with trust; the second set: entails hypotheses associated with perceived risk; and the third set: includes hypotheses associated with MFS adoption constructs. The last section of the discussion is booked for a succinct analysis of TOPSIS output obtained via the SEM-TOPSIS hybrid technique.

It should be mentioned that all hypotheses were tested when controlling for age and education. The reason for controlling variables is to support mitigating the unrelated effect. Moreover, its use improves the outcome's robustness and validity. In terms of relationships, the study accounts for the p-value column allied with each variable where the related p-value of less than 0.05 indicates a significant association. The results of the eleven hypotheses tested were statistically significant except for the relationship between perceived time risk (PTimeR) and perceived risk (PRisk, i.e., H6; see **Figure 4-2**).

The first set is hypotheses related to trust, which H1-H3 scrutinized. Empirical evidence accepts hypothesis H1 ($\beta = 0.207$, $p < 0.001$), which refers to the positive effect

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of the disposition to trust on general trust in MFS. Payne & Clark (2003) showed that the general disposition to trust exerts substantial control over senior managers' trust in an industrial context. Moreover, Consumers' disposition to trust has been revealed to strongly influence their trust in an e-vendor (McCord & Ratnasingam, 2004). Although most of the previous studies did not plainly define the direction of the impact, the present study ratifies that disposition to trust and trust is positively related to MFS. Such information supports the knowledge that consumers who unveil a greater disposition to trust will more willingly trust the e-vendor (David Gefen, 2000) compared to those who require more info (Salam et al., 2005). However, our results are contradicted by earlier e-services (Z. Liu et al., 2009), particularly in mobile banking. The reason might be that when consumers encounter a choice within MFS perspectives (mobile banking, mobile payment, mobile money), their trust disposition significantly affects the general trust, more or less that of the single type of MFS. As a result, companies dealing with MFS should be aware of this critical effect and prepare for any competitive advantage strategies in the marketplace.

H2 (β= 0.222, $p < 0.001$) tested the effect of trust in technology on trust in general, and the findings stressed that technology trust has a strong positive impact on trust. Given technological trust as a sole antecedent of trust whereby the object upon which the trust remained imparted when referring to the inert technology (Lippert & Forman, 2006), then, our empirical results are in line with previous findings in the context of mobile banking (Z. Liu et al., 2009). Furthermore, previous works (P. Pavlou & Ratnasingam, 2001) implicitly incorporated the concept of trust technology to trust with its importance being emphasized as a facilitator of e-commerce adoption.

Trust in the vendor was also found to positively influence general trust, which supports H3 (β= 0.251, $p < 0.001$). The results of this research are reliable with the previous finding that vendor trust has been defined as multi-dimensional and influential levers that the vendors could employ to build consumer trust (Nilashi et al., 2015). Vendor trust remains vital to promoting trust in changing a potential consumer from a curious viewer to one ready to perform MFS. Thoughtful discerning of the essence and antecedents of consumer trust in MFS can support e-vendors with a set of controllable, strategic levers to develop such trust, encouraging greater MFS acceptance and usage.

As a result, the lack of consumer trust (Trust Disposition, Technology Trust, and Vendor Trust) in the online environment has persisted, hampering IS adoption (Aldridge et al., 1997) and thus to MFS. All these could indicate that the consumers' espousal of MFS may be shaped accordingly.

The second set is hypotheses associated with perceived risk. From this part, perceived risk has five antecedents, such as H4 and H5-H8. The investigation of the relationship between trust and perceived risk has been one of the main issues in the development of IS (A. P. Pavlou, 2003). Our result shows that general trust negatively influences perceived risk, which supports H4 (β= -0.070, $p < 0.05$). The literature offers supportive studies on the import of this relationship (Muñoz-Leiva et al., 2017; A. P. Pavlou, 2003). Various researchers have also contributed to the belief that trust mitigates consumers' perceived risk (C. Cheung & Lee, 2000; Fukuyama, 1995; Kesharwani & Singh Bisht, 2012) and affects perceived benefit in e-commerce (Ratnasingham & Kumar, 2000). Lots of incentives that increase trust are similar incentives that reduce perceived risk. This result clarifies, to some extent, the doubt related to the direction of the causality between trust and risk, which was found deficient in the past literature (D. Gefen et al., 2003). From H5-H8, the empirical study found to patronize all the hypotheses at a different level

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of p-value, mentioning that each dimension of perceived risk positively influences the overall perceived risk except H6 (see **Figure 4-2**). At that point, the moderate to weak positive relationships between the perceived risk (aggregate) and the risk component offers further reinforcement that risk can be researched as a multidimensional phenomenon (G. W. Zikmund & Scott, 1974). These results are also consistent with Featherman & Pavlou (2003) work, which validated a majority of these antecedents as a risk dimension, therefore, being the influential element of the aggregated risk. Again, the outcomes reveal the multidimensional nature of perceived risk in information technology, mainly MFS. Boksberger et al. (2007) are supporters of these findings in the area of air travel. Again, the results show that perceived privacy risk H5 ($\beta = 0.309$, $p < 0.001$) is indeed the predominantly perceived risk dimension for the partakers of MFS, shadowed by the perceived cost H8 ($\beta = 0.146$, $p < 0.001$) and perceived security risk H7 ($\beta = 0.142$, $p < 0.001$). Moreover, this study confirms the positive effect of the perceived cost on the consumers' perceived risk, such as that the lower the cost, the more minor the perception of risk and the more the likelihood of MFS adoption. As such, the involvement aspect of the risk (Choffee & McLeod, 1973) is importantly observed when the price or cost is high, and the consumers risk losing money.

This research reveals no statistical evidence to support hypothesis H6 ($\beta = 0.032$, $p < 0.342$) that perceived time risk positively influences the aggregate perceived. Although H6 is rejected, the expected direction of the relationship is kept just that the p-value is not statistically significant at 0.05. However, our findings are controverted by prior online payment research that has indicated a positive relationship between time risk and perceived risk (L. Zhang et al., 2012). It has been stressed that consumers lack patience in waiting a long time because they always delight in pursuing new things (L. Zhang et al., 2012). Then, a longer waiting time for service delivery would deter the desire and impact their buying disposition or decision to adopt. Given this current study, the perceived risk dimension, such as perceived time risk, does not appear to impact specific information technology acceptance, at least for the Togolese MFS examined in this research. The reason may be related to the participants (user and potential user) MFS experience. Since quite many of them lack experience in MFS, they might not be conscious regarding the real time needed for a service done. Therefore, the effect of time risk perceived is worthy of further development in future studies and MFS companies are encouraged to continue easing the transaction process of MFS about time spent.

The third set is hypotheses associated with the adoption of MFS. Among them, the hypothesis associated with the positive relationship that the dispositional trust has with MFS adoption was supported by the test result; hence, H 9 ($\beta = 0.355$, $p < 0.001$) is accepted (**Figure 4-2**). This infers that when increasing the level of trust disposition, individuals tend to adopt MFS technologies without necessarily cogitating on the general trust. The finding is consistent with e-commerce adoption for SMEs (Chakuthip et al., 2007). Moreover, scholars reported that indicators for dispositional trust should be incorporated into empirical studies either as a moderating variable or as a precursor of trusting beliefs, intentions, and behaviors (Grabner-Kräuter & Kaluscha, 2003). Being an antecedent of trust, a disposition to trust remains one of the most operative elements required during the launch phases of a relationship when parties are generally unacquainted with each other (Rotter, 1971). Since MFS is still in the early adoption stage in Togo, service providers are recommended to promote the variable that could increase the consumer's dispositional trust.

From **Figure 4-3**, perceived risk significantly negates the adoption and usage of MFS,

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rendering the support of H10 (β= -0.097, $p < 0.022$). It is crucial to signpost this outcome's feasibility to be enlightened by the theory of consumer behavior (Bauer, 1960) allied with risk perception. The importance of perceived risk in the study also confirms previous studies that demonstrate that consumers' perceived risk is more efficacious at clarifying purchasing or adoption behavior inasmuch as consumers are more recurrently driven to avert mistakes than to capitalize on utility in purchasing (Mitchell, 1999). This output is also coherent with a recent report on mobile payment adoption, which underlines rapid technology innovation while stressing the importance of perceived risk in the form of security (De Fouchier & Larduinat, 2016; Manchiraju et al., 2016).

Last but not least, the study entails and accepts hypothesis H11 (β= 0.108, $p < 0.008$), in which general trust positively influences MFS adoption. Generally, trust remains a vital factor in various economic and social relations involving uncertainty and reliance (Hosmer, 1995; Rousseau et al., 1998), particularly those regarding important decisions (Luhmann, 1979) and new technology (Fukuyama, 1995) as an MFS perspective. Accordingly, our findings are sustained via the idea that trusts in business rests on the relevant and crucial stimulus of behavior in general (Konovsky & Pugh, 1994; C. M. Rossiter & Barnett, 1975; Schurr & Ozanne, 1985), and the facilitator factors for MFS adoption and usage in particular.

Under this set, it can be deduced that improving trust and decreasing risk continue to raise the likelihood level of consumers' engagement in MFS transactions. Companies are required to take the necessary precaution to balance the trade-off.

SEM-TOPSIS: It is noteworthy to recall that the second section of the discussion concerns the output of MFS alternatives computation. The overall result from the TOPSIS technique shows the preference of each alternative regarding the various sub-criteria. The relative closeness $\overline{\boldsymbol{C}_{\boldsymbol{I}}^{*}}$ results obtained satisfies the sine qua non-condition, i.e., $\mathbf{0} \leq \overline{\boldsymbol{C}_{\boldsymbol{I}}^{*}} \leq \mathbf{1}$. Furthermore, the TOPSIS technique is grounded on the principle that the higher the value of $\overline{\boldsymbol{C}_{\boldsymbol{I}}^{*}}$, the higher the rank order, the more the chosen alternatives are favored over others. The final result reveals that mobile money transfer (MMT) is the most preferable MFS to adopt and use with $\overline{\boldsymbol{C}_{\boldsymbol{I}}^{*}}$ tantamount to 0.7454 signifying 46.68% compared to the last two remainings. Mobile payment (MP), with 0.6106 (38.24%), was found to be the second MFS alternative used, whereas mobile banking (MB) adoption, with 0.2407 (15.07%), is considered minor. This finding is supported by the prior study on mobile banking and mobile payment, where 82% of participants under 35 have made mobile payments compared to 79% who used mobile banking (Fox et al., 2016). A similar past study has further shown that mobile payment usage amongst USA millennials was generally higher than that of mobile banking. The likely motive of the MFS preference acknowledged in this study can be explained based on the significant issues of concern towards perceived privacy risk. Mobile money transfers or mobile payment services do not necessarily involve consumers' personal information or an account that needs to be connected to a bank account. By that, many end-users would instead opt for mobile money transfer and mobile payment than for mobile banking.

Table 4-7 below compares the outputs of TOPSIS and AHP, revealing the same results for choosing the alternative ranking of mobile financial services (MFS). It was found that the outcomes were well-consistent and generally agreed with each other. Based on ranking the two techniques, mobile money transfer (MMT) was chosen as the most appropriate among the mobile financial services, followed by mobile payment and mobile banking. However, slight differences exist in the percentage of coefficient distribution

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amongst the classification of their alternatives. For instance, AHP reveals that MFS consumers prefer using mobile money services (i.e., the difference in the percentage of coefficient: 13.32%) compared to TOPSIS results. Contrarily, the TOPSIS result shows that consumers are more interested in using mobile payment when considering the difference in percentage sharing between the two techniques (i.e., the difference in the percentage of coefficient: 13.75%).

However, the results regarding the difference in percentage distribution of coefficient between TOPSIS and AHP in mobile banking selection remain trivial. These results stressed that MFS consumers would not prefer mobile banking if they had a choice between the proposed mobile financial services (MFS).

Table 4-7 Comparison between TOPSIS and AHP outputs

MFS Alternative	TOPSIS % distribution of coefficient	TOPSIS Rank	AHP % distribution of coefficient	AHP Rank	% Difference in the coefficient distribution	MFS Alternative
MMT	46.68%	1	60%	1	13.32%	MMT
MP	38.24%	2	24.49%	2	13.75	MP
MB	15.07%	3	15.26%	3	0.19%	MB

Note: The outputs of AHP are derived from the previous work of (Gbongli (2017).

Source: own research result

The difference between the finding of TOPSIS and AHP regarding MFS choice depends on their strengths and weaknesses, which are thoroughly pronounced in the literature (Gavade, 2014; Gbongli, 2016). For instance, the core advantages of AHP over TOPSIS can be attributed to its intuitive appeal to decision-makers and its ability to check inconsistencies. Furthermore, decision-makers find the pairwise comparison system of data input convenient and straightforward. However, applying AHP leads to the decision problem being decomposed into numerous subsystems, requiring a considerable number of pairwise comparisons. Therefore, it is a complex and time-consuming implementation. In the situation of TOPSIS, the non-linear relations between one-dimensional scores and distance ratios lead to considering both negative and positive ideal solutions. Also, in the TOPSIS framework, we can use variables with different units of measurement. It is straightforward to implement, so it is adopted when the user prefers a simpler weighting approach. However, TOPSIS, in its standard and original form, is deterministic and does not embrace uncertainty in the calculations associated with final weightings.

4.7 Conclusions

This study examined the influence of multidimensional trust and perceived risk facets at the individual level concurrently on the acceptance of mobile financial services (MFS) when prioritizing the MFS perspective. This paper aims to illuminate, to some extent, the MFS accessibility in Togo allied with the potential facilitators or inhibitor factors. Also, to evaluate them based on the consumer's experience and experts through a benchmark robust SEM-TOPSIS methodology. A qualitative study in the context of the Togolese was performed together with a literature review to derive the most probable factors that might influence the end user's perception of MFS since there was a scarcity of research investigating general trust and perceived risk antecedents. A quantitative study was then propelled to test the hypotheses formulated through the collected information obtained.

Our research model efficaciously integrates these dimensions, such as trust (dispositional, technological, and vendor trust) and perceived risk (privacy, time, security, and cost), viewed as complex multidimensional factors. The data support the study's

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assumption except for H6 (see **Figure 4-2**). Mainly, our study is partially similar to the recent study done in Ghana (the neighboring country of Togo), in which the perceived risk was related to the customer's trust in service providers regarding the adoption of mobile money (Abdul-Hamid et al., 2019). In this line, our study provides more information to the various role-players of MFS about the necessity to emphasize trust and risk at the multidimensional level while making strategic and multicriteria decision-making.

Comparing the ranking of TOPSIS with those obtained with the AHP techniques in a similar given population, the findings were consistent and generally approved with each other. However, a slight difference was found between both techniques, placing TOPSIS better suited to the problem of MFS classification for the study area. Amongst the MFS alternative, the ranking result revealed mobile money to be the preferable MFS type used, followed by mobile payment and mobile banking with a minor percentage.

4.8 Implication

4.8.1 Implication for Practice

The outcomes of this study expose and validate the factors that impact consumers' adoption of MFS. Firstly, the relative level of the path coefficients in our analysis model recommended that disposition to trust (an antecedent of trust) be the most salient factor that directly or indirectly facilitates the adoption of MFS. The perceived privacy risk (an antecedent of perceived risk) is the next influential factor; however, it hinders MFS adoption. Given that this trusting disposition is developed throughout a lifetime (Rotter, 1971) and reveals social impact over broad periods (Fukuyama, 1995), it implies that there might be a cross-cultural difference in trust. If so, MFS companies' providers must expect various levels of trust and, thus, different proportions of MFS adoption. As a deduction, companies are recommended to be acquainted with building trust-based tools and, for instance, increasing awareness and firms' reputations by keeping their promises while treating the customer as individuals, mainly in societies that acknowledge a lower level of trust. MFS service providers could meritoriously upsurge adoption behavior by publicizing the advantages of MFS to potential consumers, seeing that the findings supported trust with all of its antecedents.

Moreover, this study's finding imparts numerous risk effect concerns by modeling perceived risk with various facets. From this perspective, when companies propagandize their MFS services to ease the adoption issues, they should realistically underline a neutralizer or counterstep for those risks' perceptions. The prominence of privacy risk and financial risk in perceived cost, as confirmed by this study and other prior research (José Liébana-Cabanillas et al., 2014), signposts that customers still doubt the security of virtual transactions. For instance, these companies may stimulate a privacy risk protection strategy and grant technological support and anti-fraud to guarantee potential end-users minimal security risk. It is typical in the practice of emerging and developed countries (and it should be considered in developing countries as well) for payment service providers to try and promote trust in mobile financial services, in payments in general, as well as in other banking services by improving the general financial literacy of the population and small and medium enterprises. This is important, as those familiar with financial processes and concepts demonstrate more trust toward financial services and can better assess their risks (Kovács & Terták, 2016). An increasingly popular practice is for certain governments to aid this process through an appropriate strategy and programs that serve the execution of that strategy. Because perceived time risk did not hold

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statistical significance in Togo, this phenomenon pinpoints that using MFS has little to do with time spent. As such, service providers should preserve those features that ease the MFS application in the time frame.

Lastly, the outcome of TOPSIS through an SEM-TOPSIS integrated study specifies that mobile money transfer (MMT) is indeed the predominant mobile financial service (MFS) alternative used in Togo, followed by mobile payment (MP), while mobile banking (MB) is reflected as trifling. MFS companies should concede that consumer trust and risk with their antecedent create a tremendous barrier to MFS transactions. This study still demonstrates that mobile money transfer companies are not powerless amongst MFS companies. It provides a practical guideline for mobile financial service companies compared to the prevailing competitors within the related field, such as online banking and ATM, for constructing more trust-based strategies to manipulate favorable consumer attitudes, actions, and eventual transaction behavior whereas mitigating the perceived risk factors. Regarding MFS, companies offering mobile money transfer are suggested to sustain the adoption growth, while those performing mobile payment, mobile banking predominantly, are to bear their target consumers at the core of the business model by diversifying their market strategy.

With regard to the above, we cannot ignore the network nature of the payments market, an essential characteristic of which is that the market's dynamics (all the services provided and their prices) depend on the cooperation between many actors. This may explain why collaboration between actors plays a positive and decisive role in improving trust and encountered risks. Therefore, optimizing and maximizing the effect of traditional, individual competition on efficiency does not necessarily prevail (Divéki et al., 2010).

4.8.2 Implication for Methodology and Theory

This research remains the first to assess the multi-dimensional trust and perceived risk facet concurrently towards consumers' adoption decisions in mobile financial services while ranking their perspective.

The result will open doors for scholars to explore trust further and perceived risk antecedents. It will support the theory of trust and risk literature in general, and IT in particular since many prior studies lacked conclusive outcomes about the directivity of the causative relationship between trust and perceived risk (D. Gefen et al., 2003; Mayer et al., 1995; Rousseau et al., 1998). Our finding acknowledges trust as the potential predictor of risk in technology adoption. The scale items employed were extensively adopted from the general studies in developed countries that are allied with technology acceptance adoption behavior, trust, and perceived risk. This section provides a crucial methodological implication for the marketing scholar, who might require a hint to cross-cultural appraisal concerning the application of scales, like those established in the USA and their relevance or relatedness in Togo. Our study outcomes not only enhance the clarification of mobile financial services adoption via the effect of trust and perceived risk but also hold some strategic implications for the global expansion of managerial implementation decision tools. This study provides a benchmark integrated methodology based on an SEM-MCDM application, lacking in the adoption decision. The theoreticians and practitioners should comprehend that the prominence of the integrated SEM-TOPSIS is rooted in its robustness to test multifarious postulations made, combined with the high level of ranking the countless alternatives when multiple criteria issues arise in decision making.

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4.9 Limitations and Future Research

Notwithstanding some contributions to the literature and practical, theoretical, and methodological applications, all research unavoidably entails drawbacks that should be addressed. We expect future research will address these concerns. Our study outcomes are unique to Togo, although they are predominantly similar to IT in general and mobile financial transactions studies. A longitudinal study on our framework might need to better understand how the variables relay over time. This research found that time risk concerns are not significant antecedents of perceived risk. We hope future research will further elucidate the relationship between time risk issues and adoption behavior in other populations and circumstances. This research is projected to offer a wide-ranging, parsimonious decision-making model for MFS acceptance regarding multi-dimensional trust and perceived risk influences. However, the present model expounds only 13.1% of the variance in behavior to adopt. Future studies can incorporate additional variables, such as usefulness, perceived ease of use, and familiarity, to enhance the explanatory power. Based on the respondent's educational background, our distributed questionnaire appears limited to society's more educated and technically competent elements, who would be more inclined to accept MFS applications. Therefore, researchers interested in MFS for adoption and sustainability should focus more on the underbanked population, where illiterate people might be found in the majority. Comparison studies between statistical methods (regression or structural equation modeling (SEM)) and the MCDM method are welcome for future work.

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Chapter 5 Extended Technology Acceptance Model to Predict Mobile-Based Money Acceptance and Sustainability: A Multi-Analytical Structural Equation Modeling and Neural Network Approach

5.1 Introduction

The introduction of new technologies and innovations, coupled with increased customer demand, has led to a rapid business environment transformation, making it more dynamic. With this advancement of information and communication technology (ICT) and the advent of 3G and 4G services by telecom companies, mobile technology has become an integral part of everyday human life. Mobile services have been introduced into various areas like banking, commerce, government, and healthcare (K. K. Kapoor et al., 2015) (Connor & Reilly, 2018) (Gbongli, 2017). From this perspective, a bibliometric analysis recently performed by Hew (2017) showed an increased interest in the scientific world of mobile technology and suggested avenues for future research for mobile technologies. As businesses become complex with changing conditions and unpredictable economic climates, innovation is inevitable for businesses to remain competitive. In 2019, mobile phone users were forecast to reach 4.68 billion, increasing significantly yearly (Klapper et al., 2016). The high levels of penetration of smartphones worldwide offer significant growth opportunities for increasing mobile financial services (MFS) usage and motivating financial institutions and telecommunication service providers by providing new mobile applications to increase and satisfy their customers base (Alalwan et al., 2017) (Shaikh & Karjaluoto, 2014) (Gbongli, Dumor, et al., 2016).

The widespread adoption of mobile phones, particularly in developing countries, has enabled the rise of mobile money services, considered one type of MFS. Mobile money (m-money) is one of the crucial latest technological innovations in mobile communication technology. Introducing mobile money has brought new challenges and opportunities for businesses and individuals. Riquelme & Rios, (2010) stressed that as technology changes, financial companies, and consumers embrace the advantages of efficiencies, it conveys. Mobile users see mobile money services as an added value for carrying out various banking and non-banking activities in real-time in the highly competitive world (Alalwan et al., 2017) (A. Y. L. Chong, 2013). Mobile money, regarded as an innovative and effective means to achieve financial inclusion, is expected to provide financial services to two billion unbanked adults (Demirguc-Kunt et al., 2015) in emerging economies that lack access to affordable financial services (Klapper et al., 2016). The unbanked are those adults who are not bank account holders or do not have access to a financial institution.

For the last ten years, access to financial services by unbanked individuals has been expanding partly because of the rapid adoption of mobile money services (Demirguc-Kunt et al., 2015). Mobile money bridges the gap between the cash and digital economies, enabling those without access to banks to load cash in a mobile wallet and transact digitally using money transfers, deposits, withdrawals of money, and pay bills, to mention a few, through the mobile phone network. In developing countries, these services have been extensively successful, led by the example of the world’s leading mobile money service M-Pesa launched in Kenya in 2007 and deployed today in 8 countries. Mobile money services have tremendously impacted people’s lives, increasing financial inclusion

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and economic growth, absorbing financial shocks, and reducing poverty (Burgess & Pande, 2005) (Cull et al., 2014).

This paper examines the adoption and usage of mobile money in one of the emerging economies of the sub-Saharan West African countries, Togo, which has a population of more than 7.5 million (UNdata, 2017). The adoption of products, and customer engagement, are the leading indicators of the sustainability of the designated products (i.e., mobile money services), such that the number of active accounts is employed to comprehend how customers accept the services (Penicaud & Katakam, 2013). A service such as mobile money can be availed without internet connectivity using basic mobile phones and is considered convenient and safe. Based on the mobile money report published in 2018, Togo has made significant improvements from 2014 to 2017 since the services were launched in 2013 in the country. Under the sub-Saharan Africa category and over the period, the country obtained the best financial inclusion rate ahead of some countries, such as Côte d'Ivoire, Madagascar, Chad, or Mali (Fiacre, 2018). Noticeably, various companies in Togo attempt to encourage their customers to use mobile money for their financial transactions. The national social security fund (i.e., la Caisse Nationale de Sécurité Sociale: CNSS) admonished the various employers to pay their social security contributions via Flooz and T-Money (CNSS, 2019). Indeed, two major mobile telecommunication companies (Moov and Togocel) provide the mobile money service in Togo called Flooz and T-Money, respectively.

Although mobile money services have inherent benefits, their adoption rate in Togo has remained relatively low, indicating the need for further investigation. In 2015, approximately 67% of the Togolese population subscribed to mobile telephony, and mobile internet users doubled between 2014 and 2015. However, the consumer going banking in Togo is less than 15% (Couchoro, 2016) (Ashta et al., 2016), coupled with the mobile banking acceptance rate lower than expected, i.e., 1% (Financial Afrik, 2015). It is then rational to presume that mobile money should provide significant input to nurture the mobile financial services usage rate. In reality, this is far from being the situation. Although most financial institutions, together with the government of Togo, offer subsidies to farmers through e-wallets technology to support the digitization project on the agriculture transformation agenda (Aggarwal et al., 2010), the sustained usage of the designated technology has not grasped an adequate large scale succeeding the early adoption of such services.

Regarding their environment, grounded on the World Bank survey on mobile money financial inclusion (2018), handphone subscribers currently reach almost 80%, while the penetration rate of m- money accounted only for almost 45% in Togo, ranking behind its neighboring country Ghana (60%) (Fiacre, 2018). Therefore, the rate of mobile money acceptance in the West African nation also differs. These phenomena create a challenge both for established players and for new participants like Fintech startups. Whereas mobile money has stimulated financial inclusion for many unbanked Ghanaians, Togo lags in its mobile money acceptance rate. Early studies have investigated consumer adoption of mobile money services in Africa (including Togo) (Mothobi & Grzybowski, 2017) (Gbongli et al., 2017) (Akomea-Frimpong et al., 2019). However, limited studies have probed into factors contributing to the continued usage of mobile-based money technology and services within the underbanked and unbanked user segments.

Moreover, mobile money services remain focused on traditional offers such as money transfers, bill payments, and airtime top-ups and are not tailored enough to the demands of the low-income population (Lahaye, 2016). Many customers are reluctant to espouse

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such services due to uncertainty and technology anxiety about mobile financial services in general (L. C. Hsu et al., 2019) (Gbongli, Peng, et al., 2016). Nevertheless, similar emerging economies, including the Philippines and Kenya, have well accepted such services. In recent work, Suri & Jack (2016) stressed that M-Pesa's mobile money service lifted 2% of Kenyan households out of poverty. The literature on the espousal of mobile-based money in Togo is very scanty (Gbongli et al., 2017), and no research has been found in Togo regarding mobile money adoption using the TAM model, although this model has had extensive relevance in explaining the consumers' response to IT use and adoption (A. A. Bailey et al., 2017). Significant challenges are still delaying their disposition if digital finance is to reach its full potential in Togo. Customers are not adequately empowered to be active players in the ecosystem. All these reports led to choose Togo as a good experiment field for assessing the determinants of mobile-based money services adoption and sustainable development from the developing country context.

This study attempts to bridge the gap in the existing literature by analyzing users' perceptions of this technology while presenting a strategic framework for policymakers and practitioners to use the inherent advantages of mobile money. Since it is unclear how Togolese mobile money users perceive technology usage, hence the motivation behind this research is to assess and predict key antecedents influencing behavioral users' attitudes toward adopting mobile money services. This research differs from past studies in three ways:

First, it aims to explore the attributes that warrant the adoption and sustainability of mobile money services among both potential and actual users. Therefore, the result provides a practical analysis so that providers can understand customer behavioral intentions regarding the provided services, which helps make effective decisions.

Second, the study empirically creates a framework to test the applicability of the TAM to the mobile money transfer context as it is a useful research model to explain the internal and external motivation in initiating technology adoption (Davis, 1989). TAM has been utilized successfully in assessing the antecedents that drive the adoption of several technologies. The projected model has similarity to earlier extended TAMs used in developed countries: acceptance of self-service technology (SST) by French consumers (Demoulin & Djelassi, 2016) and assessing the adoption of mobile payment through US consumers (A. A. Bailey et al., 2017). We utilize the TAM from the perspective of developing countries and incorporate into the model mobile money self-efficacy, new technology anxiety, and personal innovativeness of IT. The effect of these constructs on the core TAM variables (perceived ease-of-use and perceived usefulness) is examined, as they are likely to impact the perceived ease-of-use and perceived usefulness on mobile money attitude and mobile money use intention.

Finally, this study aims to use an innovative research methodology presented in a two-stage approach. In the first stage, a structural equation model (SEM) is adopted to understand the significant influence of antecedents on mobile money services acceptance. The second stage used an artificial neural network (ANN) model to identify the importance of the antecedents. Therefore, this study develops a more inclusive and predictive model that can overcome the essential drawback of the prevailing model and offer a predictive analysis of the user perceptions of mobile money adoption in developing economies.

This research makes several contributions about an evolving market and technology to researchers, the literature on innovation systems, and financial inclusion for developing

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countries, financial institutions, users, and government by exploring and discussing direct implications for m- money role players.

This study further enlightens the attitude of the Togolese consumer of mobile data services in general and the usage of mobile-based phones for financial services specifically. Primarily, we offer nuanced empirical outcomes on the fundamental factors that drive the success or failure of mobile money innovations by extending the traditional TAM. Given the result of the integrated methodology and the variables of TAM, the perception of ease of use is revealed to be the most crucial predictor, followed by the perceived usefulness of mobile-based money regarding the attitude constructs. It is then important that mobile money transfer providers consider how to use the services easily and emphasize building user-centric apps to create awareness of usefulness. Considering the extended variables associated with TAM, personal innovativeness acts as an enabler of user behavior, and company providers require to stimulate this aspect to facilitate the usage of mobile money services. Therefore, these implications could lead to increased financial transactions on mobile devices. The contributions go along the way to extend the understanding of TAM to recently emerging contexts such as mobile-based money in Togo.

Moreover, this research provides a robust tool combining SEM and ANN to predict the determinants more prone to the adoption and sustainability of mobile-based money services. Unlike earlier research that studied consumer behaviors using a single approach (e.g., SEM), our study applied an SEM-artificial neural network technique to explain consumer behaviors regarding m-money. The SEM–ANN methodology is a powerful technique, as it examines and provides the “what” and the “why” factors that have affected or will affect the future. The result shows that SEM and ANN analyses complemented each other in shedding light on the complex process associated with the various influential factors in developing mobile money innovations. Our SEM analysis contributes to understanding the relationships between the various factors. One of the most substantial attributes of ANNs remains to be adjusted to periodic variations and detecting patterns in intricate natural nonlinear schemes. Therefore, the study results prove ANN to better predict than the usage of the SEM technique regarding the adoption of m-money. Correspondingly, this research can grasp the advantages of both methods (multi-analytic method: SEM-ANN) and assess complex linear and non-linear associations along with ranking the relative importance of the predictors.

After providing the rationale and objectives of this research, the paper is structured in the following manner: Firstly, we present the contextual setting as a literature review, discuss the development of hypotheses, and introduce the research model. Next, we outline the research methodology, which includes background on SEM-ANN analysis. Finally, we discuss the findings, implications, limitations, and future research opportunities related to the adoption and sustainability of mobile-based money services.

5.2 Literature Review and Hypothesis Development

5.2.1 Mobile Money in the Context of Mobile Financial Services

The interest manifested in the growth of inclusion has been captured by the advent of money transfer services offered over mobile phones and the further potential this technology provided for financial service development (J. C. Aker & Mbiti, 2010). Mobile money services accelerate the speed of money transfers as funds move electronically instead of in physical form (Morawczynski, 2009). Mobile money transfer is a service for transferring money through mobile phone-based (Upadhyay & Jahanyan,

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2016). Mobile money employs non-banking IT tools and channels to extend financial services access to subscribers who cannot be attained by banks (Upadhyay & Jahanyan, 2016). Although past research reveals that people tend to prefer mobile financial services (MFS) over other self-service technology (SST) in Togo (Gbongli, 2016), due to the purpose of this study, one should focus merely on the mobile money service, which is one type of MFS (Gbongli, 2017). Traditional banks continue to offer their mobile banking service and facility; however, it is important to enlighten on the difference between mobile banking, mobile payment, and mobile money.

Considering mobile banking and mobile payments, consumers needed to have a bank account in the back end. In the context of mobile banking, there are also various applications provided by banks, which can be installed on a wide range of mobile platforms and can efficiently be utilized. The transactions are done between the customer and the bank; alternatively, it may be a customer to another third party, yet the bank intermediates between them. The communication channel might be different, such as a customer, and the third party may be subscribers to different internet mobile service companies. Mobile payment involves the transfer of money (e-money) from one party (e.g., consumer) to another party (e.g., merchant or seller) employing a mobile-based device (Chandra et al., 2010). It is an add-on service on mobile technology to ease fund transfers between individuals and/or merchants.

From the perspective of mobile money, the process differs. Monetary transactions occur between two parties (users and merchants), subscribers of a similar mobile money service in the same service provider’s domain. For transferring money, a mobile phone user registers with a mobile money agent and then deposits cash that will be used for the later transaction (Bisht & Mishra, 2016). The authorized agent handles the monetary transactions between the parties. This cash is shown as e-money in a mobile wallet on the sender’s phone (Morawczynski, 2009). The customer can then use her/his electronic money to perform transactions like sending money and paying bills (Gbongli et al., 2017) (Demirgüç-Kunt & Klapper, 2013). Once a user transfers money to another mobile phone, the receiver obtains a prompt notification with a unique code through a short message service (SMS). The recipient can visit the closest agent to collect the cash; otherwise, keep the money as a deposit in her or his e-wallet for future transactions (Lashitew et al., 2019). Regarding mobile money, customers typically require not to have bank accounts in the back end. Therefore, the costs to access the designated service and switch between service providers are significantly lower than that of mobile banking and mobile payment, which might have theoretical implications for user demands.

5.2.2 An Extended TAM and Mobile Money Transfer Services

To understand user behavior toward the adoption of innovative technology, academicians have developed various behavioral decision theories and intentional models over the last four decades. Studies included variables from the most prominent theories and models, including the theory of reasoned action (TRA), the theory of innovation diffusion (IDT), the technology acceptance model (TAM), the theory of planned behavior (TPB), and the unified theory of acceptance and use of technology (Khalilzadeh et al., 2017) (P. P. Patil et al., 2017) (Shen et al., 2017) (Francisco Liébana-Cabanillas, Marinkovic, et al., 2018) (Francisco Liébana-Cabanillas, Muñoz-Leiva, et al., 2018).

Within the Information Systems (IS) literature, models such as the TAM (Davis et al., 1989) have been employed to explore technology acceptance factors empirically. Grounded on the objectives of this study, and due to the importance of explaining online consumer behavior, we have employed attitudinal models and theories based on social

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psychology, like TAM (Davis et al., 1989). TAM is one of the most widely used theories in IS research. It has been considered the most robust, parsimonious, and persuasive model in innovations acceptance behavior (Davis et al., 1989) (A. P. Pavlou, 2003), and thus, we consider this theoretical model as a background for the drive of the present study. The TAM model positioned attitude toward using new technology as a construct explained by two perceived variables: usefulness and ease-of-use. Various studies apply the TAM model to predict intentions to adopt new technology by individuals, groups, or organizations (Davis et al., 1989). Drawing on the theory of reasoned action (TRA) (I. Ajzen & Fishbein, 1975) and its simplest form, TAM suggests that perceived ease-of-use, perceived usefulness, attitude regarding use, and behavioral intention will predict actual usage of technology. Additionally, the TAM has been contingent on numerous additions and developments, including the unified theory of the acceptance and use of technology (UTAUT) (Venkatesh et al., 2003b).

With the review of TAM literature, Marangunić & Granić (2015) have acknowledged seven past TAM-related works. The objectives of these works and the analysis techniques employed differ. For instance, Legris et al. (2003) and Turner et al. (2010) examine the question of whether the TAM explains actual use, Hsiao & Yang (2011) investigated factor analysis to find trends in the usage of the TAM, whereas Mortenson & Vidgen (2016) conducted the review using the computational literature review (CLR) based on the TAM. The CLR answers the challenge encountered in selecting, filtering, and analyzing large volumes of research articles. It complements rather than substitutes the human researcher in the systematic literature review (SLR) process, and it is beneficial for more generic analysis of journals and individual researchers and teams. TAM has also been applied and empirically supported in the prediction of the adoption of E-commerce (A. P. Pavlou, 2003), mobile marketing (Sultan et al., 2009), mobile wallets (Shin, 2009), e-learning (Abdullah & Ward, 2016); mobile banking (Isaac et al., 2018), Big Data (Okcu et al., 2019), business-related technologies (Kalinic et al., 2019) and much other information. Considering the performance of the mobile-money business and the various determinants from the literature, empirically examining some key factors will be prudent. Hence, Narteh et al. (2017) assessed the effect of eight exogenous constructs, including perceived (usefulness, ease-of-use, risk, trust, complexity, cost of use), social influence, and relative advantage on the behavioral intentions of users of mobile money services. The results revealed that perceived (usefulness, ease-of-use, trust, cost of use) and social influence significantly contribute to mobile money technology adoption (Narteh et al., 2017). Many studies have patronized TAM's explanatory power within the context of IS application in general (Venkatesh & Bala, 2008), and several studies have successfully extended its application to the context of mobile financial services (A. A. Bailey et al., 2017) (Muñoz-Leiva et al., 2017) (Malaquias & Hwang, 2019).

Despite recent and various extensions of the Davis et al. (1989) technology acceptance model (TAM), just a few studies have focused on the factors that influence the acceptance of mobile-based money services from a holistic approach integrating several principles (Chauhan, 2015). In order to bridge the gap, the proposed, tested model in this research integrates individual difference factors, considering earlier criticism that TAM suffered from the lack of individual difference factors and the inclusion of these features by researchers who proposed extended models (A. A. Bailey et al., 2017) (Demoulin & Djelassi, 2016) (Venkatesh & Bala, 2008). Based on the above discussion and the result of the pretest that probed respondents regarding the factors that would either drive or hinder their use of mobile money transfer, the study integrates mobile money transfer

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self-efficacy, technology anxiety, and personal innovativeness of information technology with the TAM variables. These factors have not only been revealed to be significant in prior research but also their theoretical foundations are rooted in some of the most influential theories and models in the field of technology adoption. Variables such as perceived usefulness, perceived ease of use, attitude, and intention to use are adopted from the TAM (Davis et al., 1989).

Additionally, self-efficacy and its role in technology acceptance have been an aspect of the investigation on the acceptance of various technologies (A. A. Bailey et al., 2017) (K. Yang, 2010) (Lewis & Loker, 2014) (Joo et al., 2018) (Balapour et al., 2019). New technology anxiety and personal innovativeness in information technology, which have also been factored into the rate of acceptance of new technology, are adopted from the literature on information technology (Demoulin & Djelassi, 2016) (J. K. Park et al., 2019) (Upadhyay & Jahanyan, 2016). The relationships between the variables will be explained in detail in the next section.

5.2.3 Mobile money self-efficacy (SEMM)

Self-efficacy denotes a self-confidence regarding the possession of the required skills to complete a task; it is the people's judgment of their capabilities to organize and execute courses of action required to attain designated types of performances (Bandura, 1997). Dominant in Bandura's concept of self-efficacy, it is the clue that this personal belief remains the main basis and a direct element of an individual's behavior and actions. It conceptualizes the individual perception of internal control (Venkatesh, 2000) (Taylor & Todd, 1995a). This implies that mobile money services consumers are more likely to pursue activities within their arrays of perceived competencies, and is an important factor in understanding individual responses to new technology (Lewis & Loker, 2014). Self-efficacy has been included in studies of the acceptance of mobile data services (K. Yang, 2010); online shopping (Faqih, 2013); and information communication of technology (ICT) (Hatlevik et al., 2018), particularly in mobile money transfer (Baganzi & Lau, 2017). Therefore, the following hypotheses are presented:

H1a. M-money self-efficacy has a significant link on perceived ease-of-use of m-money service.

H1b. M-money self-efficacy has a significant link on m-money perceived usefulness.

5.2.4 New technology anxiety (TAMM)

Technology anxiety is an apprehensive belief showing the consumer's state of mind concerning his ability and willingness to adapt when considering using technology in general (Venkatesh & Bala, 2008) (Meuter et al., 2003). Fast changes in technology bring challenges to companies due to consumers' resistance to espousing new technology (Fournier & Mick, 1998). In the transition to new technology products, consumers might come across various difficulties, such as unable to operate products correctly (Cui et al., 2009) (Parasuraman, 2000), which results lead to technology anxiety. Technology anxiety, conceived as an anchoring belief, impact the perceived ease-of-use of a system (Venkatesh & Bala, 2008) (Venkatesh & Davis, 2000); therefore, customers who are anxious about the application of IT may not perceive mobile money transfer as easy to use. Technology anxiety has a negative influence on the acceptance of self-service technology (SST) usage (Demoulin & Djelassi, 2016) and the adoption of new technological forms, such as mobile service industries (L. C. Hsu et al., 2019). Hence, we proposed the following hypotheses:

H2a. Technology anxiety has a significant link on m-money perceived ease-of-use.

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H2b. Technology anxiety has a significant link on m-money perceived usefulness.

5.2.5 Perceived ease-of-use (PEMM), perceived usefulness (PUMM), and attitudes (ATMM) toward mobile money services

The traditional TAM integrates perceived ease-of-use (PE) of technology and perceived usefulness (PU) of the technology as two main constructs. Alike with the concept in Davis et al. (Davis et al., 1989), PU in this research denotes the extent to which a person believes that using mobile money will enhance his or her performance. Mobile money is supposed to provide diverse benefits to its users such as general convenience, simplification of payment as compared to other forms of payments, all of which might endorse a positive attitude towards and a higher intention to use mobile-based money transfer payment (Chauhan, 2015). PE of mobile money denotes the consumers' perception of the effort and time that has to be expended in to use mobile money service and the degree to which the technology is understandable or not. The mobile money interface should be simple and easy to comprehend, considering the low rate of technological sophistication and literacy rates in Togo (Mas & Morawczynski, 2009). Previous studies have consistently recognized PE to have direct effects on PU and attitude (Chauhan, 2015) (Yousafzai et al., 2007). A study employing TAM reveals that there is a positive relationship between PU and PE (Van der Heijden, 2003) (K. Yang, 2012). The ease-of-use of a mobile money system can impact its usefulness and user's attitude. Hence, the following hypotheses are posited as follow:

H3a. M-money perceived ease-of-use has a significant link on attitude towards m-money.

H3b. M-money perceived ease-of-use has a significant link on m-money perceived usefulness.

H4. M-money perceived usefulness has a significant link on attitude towards m-money.

5.2.6 Personal innovativeness (PIMM)

Agarwal and Prasad (Ritu Agarwal & Karahanna, 2000) (p. 206) explained personal innovativeness as "the willingness of an individual to try out any new information technology"; it remains conceptualized as an attribute being not impacted by environmental or internal factors. Individual innovativeness prevails as a determined trait that is reflective of an individual's primary nature when exposed to innovation (Yi et al., 2006). Innovativeness can be grouped under the personality characteristics that outline the degree to which individuals accept and adopt new ideas, products, and systems (Midgley, 1978). It has been used to predict technological innovations' adoption among consumers (Wood & Swait, 2002). Towards the innovation diffusion concepts (Rogers, 2003) people react differently to a novel idea, practice, or object due to their differences in individual innovativeness, a willing tendency regarding adopting an innovation. In the earlier work, J. Fang et al. (2009) assessed the psychological variables (trust in sponsor and personal web innovativeness) entail in a decision for or against participation in web surveys. Their findings revealed that both variables exerted direct determinant effects rather than moderate effects on participation attitude and perceived behavioral control, which in turn significantly influenced participation intention. From this end, personal innovativeness would influence attitude and intention in the context of consumer participation in mobile money services.

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Several empirical studies have found a significant relationship between personal innovativeness and behavioral intention (Lian & Lin, 2008) (G. W. H. Tan et al., 2014). Thus, we propose:

H5a. Personal innovativeness has a significant link on the attitude of using m-money.

H5b. Personal innovativeness has a significant link on the intention of using m-money.

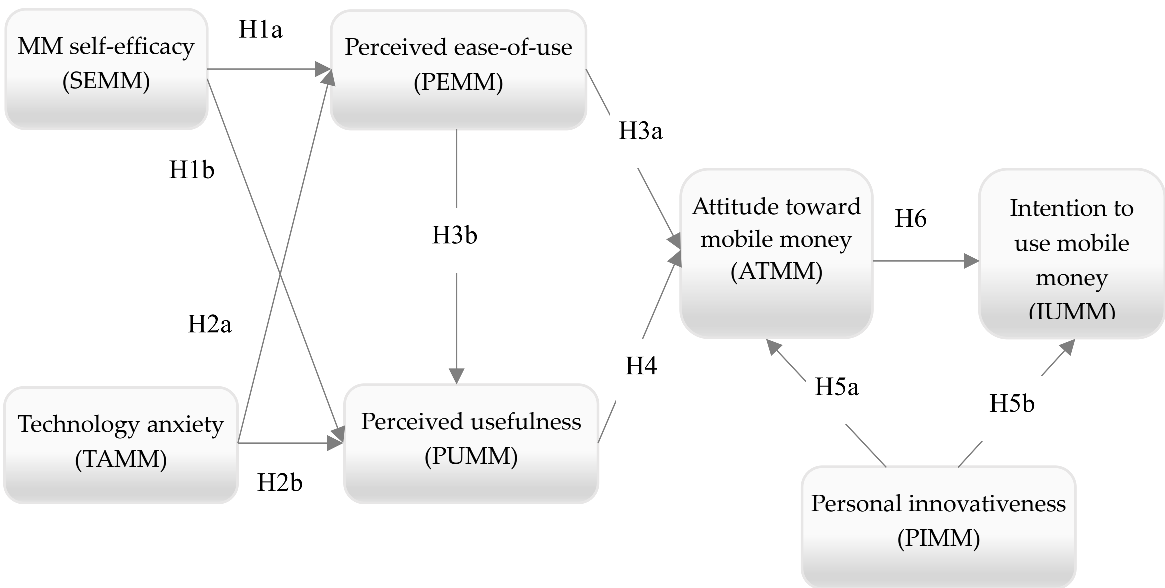
5.2.7 Attitudes (ATMM) and intentions of use (IUMM)

The relationship between attitude and intention emphasized in the TAM proposes that attitude acts as an evaluative predisposition to behavior. The attitude towards using mobile money transfer (MMT) has been considered as the extent to which an individual perceives a positive or negative feeling related to MMT. Prior studies on TAM and in other consumer fields have found a link between attitudes and intentions (Yousafzai et al., 2007) (K. Yang & Jolly, 2009). A plethora of studies established that consumers with a positive attitude towards a technology incline to have a higher intention to use it (Marangunić & Granić, 2015) (Tao et al., 2018). Indeed, past studies have been confirmed attitude as the most influential predictor of intention to use IT in the original TAM (Yousafzai et al., 2007) (Teo & Zhou, 2014) (B. Wu & Chen, 2017). From this perspective, it is highly important to educate the users of mobile money at the point of sale. Based on these discussions, we, therefore, posit that:

H6. Attitude towards m-money has a significant link on m-money behavioral intention.

5.2.8 Research Hypotheses

Based on the theoretical foundation of TAM, we propose a research model that incorporates mobile money self-efficacy (SEMM), new technology anxiety (TAMM), and personal innovativeness (PIMM) as predictors of mobile money transfer (MMT) users' attitudes and intentions. The ANN technique categorizes the research model into fourfold (models A, B, C, and D). The relationships between these constructs and groups are integrated into the conceptual model shown in Figure 5-1.



Notes: **Model: A** (Input neuron: SEMM, TAMM; Output neuron: PEMM). **Model: B** (Input neuron: SEMM, PEMM; Output neuron: PUMM). **Model: C** (Input neuron: PEMM, PUMM, PIMM; Output neuron: ATMM). **Model: D** (Input neuron: PIMM, ATMM; Output neuron: IUMM).

Figure 5-1 Proposed research model
Source: own elaboration

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5.3 Research Methodology

5.3.1 Variable Measurement

A list of components was created, which examined the underlying dimensions of each construct. This list was based on a review of previous literature and input from a small group of experts in the mobile payment field and experienced mobile money users who ultimately selected the relevant components (J. R. Rossiter, 2002). Their suggestions were used to adapt the wording and some of the most recognized scales to tailor them to the current context.

Specifically, we revised the new technology anxiety (TAMM) scale, which reflected consumers' apprehensions and fears concerning using technology, from Meuter et al. (2003) and J. K. Park et al. (2019). Self-efficacy (SEMM) is adapted from Venkatesh & Bala (2008). The personal innovativeness (PIMM) scale was adapted from Ritu Agarwal & Prasa (1998), Flynn & Goldsmith (1993), and Kalinic et al. (2019). The perceived ease-of-use (PEMM) scales follow similar scales employed by Kalinic et al. (2019), Venkatesh & Davis (2000), and Upadhyay & Jahanyan (2016a). The Perceived usefulness (PUMM) scale was adapted from Kalinic et al. (2019) and F. D. Davis et al. (1989). The attitude (ATMM) scales drew on established scales from the consumer behavior literature MacKenzie & Lutz (1989) Lafferty et al. (2015). Lastly, items of usage intention (IUMM) are adopted from Venkatesh (2000) and Venkatesh & Davis (2000). The scales were all measured in 5-point Likert scales anchored between 1 (totally disagree) and 5 (totally agree), except for Attitude, which was based on a 5-point semantic differential scale. Appendix B offers more information about constructs.

The second part of the questionnaire included questions concerning respondents' socio-demographic characteristics and behavior (i.e., gender, educational qualifications, age, and respondents' experience with mobile money transfer). The adapted questionnaire was tested for its face validity among eight experts. Changes were included grounded on the experts' recommendations, and the questionnaire was therefore employed for pretesting.

5.3.2 Pretesting the Questionnaire

There were 32 items engendered and screened through an iterative process that employed item-total correlations and explorative factor analysis (Steenkamp & van Trijp, 1991). A pre-test of all items was done on a sample of 97 participants (e.g., academic experts and graduate students) to confirm that their meaning and understanding were clear and to determine the time taken to complete the questionnaire. This pilot study's outcomes prompt minor revisions of the questionnaire's wording and diminish the original 32 items to 24. Therefore, the test result of the purified items revealed that Cronbach's alpha was above 0.70, regarded as acceptable for unidimensionality. The factor loadings were greater than or equal to 0.60 (Steenkamp & van Trijp, 1991). Per the revised 24 items accessible, data were collected for 510 individuals.

5.3.3 Sampling and Data Collection

The main objective of this study is to investigate the relationship between various constructs, such as intentions and attitudes, and expand on the traditional Technology Acceptance Model (TAM) to mobile money services. The study is based on survey data gathered from users of mobile money services in Lomé, the capital city of Togo. Lomé is known for being the most bustling and populated district in Togo, with the largest concentration of mobile money agents, and serves as the country's primary economic hub.

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A purposive sampling technique was applied to select the various study areas, and simple random sampling was employed to sample the subscribers. The purposive sampling method was employed to sample the district business units since the majority of users of mobile money services reside in these areas. The application of the simple random technique was to offer an equal chance to the users of the service. This occurred by randomly selecting users physically present at each business/service center until designated members or units were chosen. The questionnaire was administered directly, and the samples were contacted directly.

The study took several steps to ensure the quality of the data. Firstly, the research objectives were clearly explained to participants before each interview, and confidentiality of the collected data was assured, with the data being used solely for research purposes. The questionnaire used in the study was originally in English and was translated into French, the official language of Togo, by two bilingual IT professionals with extensive experience in mobile money services. Conceptual rather than literal translations were emphasized, and the questionnaire was translated into simple French, with a reading level equivalent to that of a 6th grader, to improve comprehension for the general population. After the initial translation, both translators and the researcher, who was bilingual in French and English, convened to reconcile any discrepancies and integrate the translations into a single version. The primary data was collected through a structured questionnaire administered in French to prospective and current mobile money users. Literate participants completed the questionnaire on their own, while assistance was provided to illiterate participants. The questionnaire took approximately 10-15 minutes to complete. Finally, the collected questionnaire was retranslated from French to English following the same translation procedure for the data analysis.

Hinkin (1995) suggests that an ideal sample size should have a proportion of item-to-response ranging from 1:4 to 1:10 for each set of scales to be factor analyzed. Since this study includes 24 items (refer to Appendix B), an appropriate sample size would be between 96 and 240 participants for adequate factor analysis. After excluding incomplete returns and missing responses in the scale and demographic sections, 539 were deemed usable for analysis (J.F. Hair et al., 2017). **Table 5-1** presents the descriptive statistics of the sample.

Out of the participants in the survey, 53.2% were female, and 46.8% were male. The age distribution was as follows: 14.1% were under 18 years old, 26.9% were aged 19-24, 36.9% were aged 25-30, and the remaining participants were over 31. The majority of respondents had a high school certificate or below, i.e., a Baccalaureate (49.7%), followed by an Undergraduate degree (37.7%), a Master's degree (10.7%), and Doctorate (2%). Most of the participants in this study were mobile money users, with 38.6% having less than one year of experience, 25.2% having one to two years of experience, and 6.7% having three to four years of experience. Additionally, 6.5% of respondents reported having five or more years of experience, while 23% had no mobile money experience. Table 5-1 summarizes the demographic variables of the analyzed sample.

Table 5-1 Demographic information of respondents (n = 539)

Respondents' Profile		Number	Rate (%)
Gender	Women	287	53.2
	Men	252	46.8
Age	Under 18	76	14.1
	19-24	145	26.9
	25-30	199	36.9
	31 and over	119	22.1

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To continue **Table 5-1** Demographic information of respondents (n = 539)

Respondents' Profile		Number	Rate (%)
Education	A Level	268	49.7
	Undergraduate	203	37.7
	Graduate	57	10.6
	Doctorate	11	2.0
Prior mobile money experience	none	124	23.0
	1 Year	208	38.6
	1-2 Years	136	25.2
	3-4 Years	36	6.7
	5 Years	35	6.5

Source: own research result

5.3.4 Common Method Bias (CMB)

Employing a questionnaire in the behavioral study is regarded as a standard technique to collect data and conduct the analysis. This approach leads to a standard method by which the variance and measurement error can be assessed (Podsakoff et al., 2003). Moreover, common method bias is viewed as a potential issue in social research and thus might mitigate or weaken the credibility of the data analysis outcomes (Podsakoff et al., 2003) (N. K. Malhotra et al., 2006). Concern arose that CMB may have inflated the outcomes in the study, particularly the relationships between the variables, due to the self-reported data employed while the survey partakers simultaneously responded to the items in a single questionnaire (Conway & Lance, 2010). In addressing this concern, a common scale was implemented in this research in the form of two broad tests such as Harman's single-factor analysis and the unmeasured latent marker construct (ULMC) (Harman, 1976) (Sun et al., 2015).

The guidelines suggested that the single factor should be extracted if there is less than a 50% variance to determine the controlled level of CMB within the research's constructs (Podsakoff et al., 2003). In this study, the result of Harman's single-factor test revealed that the largest variance explained by individual factors accounted for 22.94%. This is lower than the threshold value (50%) of the total variance explained. Therefore, none of the factors can explain the majority of the variance; such result shows evidence of no common method bias in this study.

The ULMC technique compared the coefficient of determination (R^2) with a CMB construct to the R^2 without a CMB construct and indicated that ULMC explained only 5.28% average variance of the measures, and their related construct explained 78.9%. This outcome also indicates that CMB is not a significant problem in the study (Podsakoff & Organ, 1986).

5.3.5 SEM-Artificial Neural Network Approach

The methodology used in this study is comparable to the earlier studies (Francisco Liébana-Cabanillas, Marinkovic, et al., 2018) (A. Y. L. Chong, 2013) (Francisco Liébana-Cabanillas et al., 2017) (Sujeet Kumar Sharma, 2019) to validate the research model and test the suggested research hypotheses. There are two stages in data analysis. During the first stage, the structural equation model (SEM) is used to understand the significant influence of predictors on mobile money transfer (MMT) acceptance. The second stage adopted an artificial neural network (ANN) model to identify the importance of the predictors. Therefore, the performance results between the two approaches will be checked to determine whether there are differences in determinants predicting the adoption of mobile money transfers.

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Given that SEM is generally applied to verify hypothesized relationships, it has seldom been integrated with other artificial intelligence algorithms (C. I. Hsu et al., 2009) (T. C. Wong et al., 2011) when users are making technology adoption decisions; SEM may often oversimplify the complexities involved as it is merely detecting linear model. An SEM-ANN technique was booked to address this challenge since ANN detects linear and non-linear relationships without necessitating any distribution assumptions, including normality, linearity, or homoscedasticity (L. Y. Leong et al., 2013). Another advantage offers using ANN resides in its ability to perform more accurate predictions in comparison to traditional regression techniques such as multiple regression analysis (MRA), multiple discriminant analysis (MDA), or SEM (Morris et al., 2003). Contrarily, the neural network also presents some drawbacks. Due to the ‘‘black-box’’ approach related to its application, ANN is unsuitable for testing hypotheses of causal relationships (L.-Y. Leong et al., 2013). When analyzing a model, it is often difficult for researchers to understand how the neural nets arrive at their results (Garson, 1998). To overcome these issues, significant variables derived from SEM are used as the input units to the ANN (G. W. H. Tan et al., 2014). This is one of the few mobile money adoptions and sustainability studies which combine SEM with ANN by taking a developing country context.

5.4 Structural Equation Modeling (SEM) Analysis

Figure 5-1 depicts that the research model was analyzed by employing structural equation modeling (SEM). We used a two-step modeling process proposed by Anderson and Gerbing (J. C. Anderson & Gerbing, 1988) for data analysis. Step one involves the measurement model analysis, whereas step two tests the structural model (including hypothesis testing).

Particularly, with the help of the SmartPLS 3.2.8 statistical package, the PLS-SEM technique was employed to perform the SEM analysis in this study. Because of focusing on analyzing key sources of explanation for a certain target construct, PLS-SEM is mainly used in exploratory research and theory development (J.F. Hair et al., 2017) (Kline, 2015). From the recommendation of Chin and Newsted (W.W. Chin & Newsted, 1999), the PLS method places fewer boundaries on the measurement scales, residual distribution, and sample size and is appropriate for our explorative study. Compared with other SEM methods, the strength of this approach resides in its flexibility for distributional assumptions and handling complex predictive models (W.W. Chin & Newsted, 1999). In most consumer behavior research, the data are non-normal, and PLS is unbound by the normality assumption (J. Lu et al., 2017) that is necessitated in covariance-based SEM (Vuong et al., 2019). Moreover, the estimates of mediation effects obtained by PLS are more accurate, and the method accounts for measurement errors (W.W. Chin, 1998).

5.4.1 Measurement Model Assessment

We conducted a confirmatory factor analysis (CFA) to validate the measurement model regarding the observed variables' reliability, internal consistency, and validity (Ho, 2013). Consistency evaluations are grounded on single observed and construct reliability tests, while convergent and discriminant validity are employed for assessing validity (Joe F. Hair et al., 2012). The observed variables with an outer loading of 0.7 or greater are considered greatly acceptable (Joe F. Hair et al., 2012), whereas the outer loading of a value less than 0.7 should be rejected (WW Chin, 1998). From this perspective, the cut-off value accepted for the outer loading was 0.7 in this research.

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From **Table 5-2**, the outer loadings ranged between 0.717 and 0.942. We employed Cronbach's alpha and Composite Reliability (CR) to assess the internal consistency in the construct reliability. Compared to Cronbach's alpha, CR is regarded as a better assessment criterion for internal consistency since it retains the standardized loadings of the observed variables (Fornell & Larcker, 1981). However, Cronbach's alpha and CR values were used in this study. All Cronbach's alpha and CR values are greater than 0.8 (See **Table 5-2**). We, therefore, concluded that all indicators are reasonably reliable and indicated that all the latent construct values exceeded the minimum threshold level of 0.70 (Bagozzi et al., 1988).

Both convergent and discriminant validity are employed to assess the validity of constructs. The examination of the convergent validity is grounded on average variance extracted (AVE) values as an evaluation criterion (Ketchen, 2013). **Table 5-2** shows that all the AVE values were more than 0.5, aligning with the threshold Fornell & Larcker (1981) recommended. Therefore, convergent validity was sufficient for this study model, indicating that each latent variable explained more than 50% of their indicator's variance on average.

The subsequent computation was the discriminant validity of the latent constructs. Discriminant validity describes that the manifest variable in any construct differs from other constructs in the path model, where its cross-loading value in the latent variable is greater than that in any other constructs (Sarstedt et al., 2014). The Fornell and Larcker criterion and cross-loadings were employed to estimate this study's discriminant validity (Fornell & Larcker, 1981). The recommended standard is not to have a construct displaying the same variance as any other construct with more than its AVE value (Sarstedt et al., 2014). **Table 5-3** shows the model's Fornell and Larcker criterion test, where the squared correlations were compared with those from other latent constructs. **Table 5-3** displays that all correlations were smaller relative to the square root of average variance employed along the diagonals, suggesting satisfactory discriminant validity. Furthermore, the investigation of cross-factor loadings in **Table 5-4** demonstrates the appropriate discriminant validity, as the loading of every indicator on the allocated construct exceeds its loading on other constructs (W.W. Chin, 1998). Therefore, the discriminant validity of the study constructs is acceptable.

Considering endogeneity is essential when applying regression-based techniques such as PLS-SEM (Hult et al., 2018) since we can never exhaust all the determinants affecting users or potential users of mobile money services. We used an instrumental variable approach following the guideline Kock (2017) recommended to test and control for endogeneity in PLS-SEM, in which the instrumental variable should have a direct link to the independent variable but not to the structural dependent variables. Notably, the study tested the endogeneity in the outcome variable (Weerawardena et al., 2015), i.e., mobile money usage intention (IUMM). The endogeneity was assessed based on the two endogenous variables, perceived ease-of-use mobile money (PEMM) and mobile money perceived usefulness (PUMM). For PEMM-IUMM, the estimate of an instrumental variable called iPEMM-IUMM revealed a path coefficient $\beta=0.056$ and p-value=$0.097>0.05$. For PUMM-IUMM, the estimate of the instrumental variable called iPUMM-IUMM is $\beta= 0.071$, p-value=$0.051>0.05$. Since the instrumental variables are significantly higher than 0.05, we conclude that endogeneity bias may not be an issue in this research. Therefore, it does not influence the structural model's robustness that generated this study's results.

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Table 5-2 Construct reliability and validity

Constructs	Items	Loadings[1]	AVE[2]	CR[3]	α[4]
Mobile money self-efficacy (SEMM)	SEMM1	0.922	0.745	0.897	0.85
	SEMM2	0.817			
	SEMM4	0.846			
Mobile money technology anxiety (TAMM)	TAMM1	0.935	0.821	0.932	0.896
	TAMM2	0.838			
	TAMM3	0.942			
Perceived ease-of-use mobile money (PEMM)	PEMM1	0.885	0.744	0.897	0.828
	PEMM2	0.91			
	PEMM3	0.789			
Mobile money perceived usefulness (PUMM)	PUMM1	0.879	0.726	0.888	0.815
	PUMM2	0.887			
	PUMM3	0.786			
Attitude toward mobile money (ATMM)	ATMM1	0.87	0.662	0.886	0.83
	ATMM2	0.829			
	ATMM3	0.795			
	ATMM4	0.755			
Personal innovativeness in mobile money (PIMM)	PIMM1	0.847	0.67	0.89	0.838
	PIMM2	0.811			
	PIMM3	0.717			
	PIMM4	0.891			
Mobile money usage intention (IUMM)	IUMM1	0.852	0.72	0.911	0.871
	IUMM2	0.889			
	IUMM3	0.765			
	IUMM4	0.882			

[1]All item Loading > 0.5 indicates indicator Reliability (Hulland, 1999); [2]All Average Variance Extracted (AVE)> 0.5 as an indication of Convergent Reliability (Bagozzi et al., 1988); [3]All Composite Reliability (CR)>0.7 indicates internal Consistency (David Gefen, Straub, & Boudreau, 2000); [4]All Cronbach's alpha > 0.7 indicates indicator Reliability (Bernstein & Nunnally, 1994).

Source: own research result

Table 5-3 Discriminant validity (Fornell–Larcker criterion test)

Constructs	ATMM	SEMM	TAMM	IUMM	PEMM	PUMM	PIMM
Attitude toward mobile money (ATMM)	**0.814**						
Mobile money self-efficacy (SEMM)	0.245	**0.863**					
Mobile money technology anxiety (TAMM)	0.174	0.03	**0.906**				
Mobile money usage intention (IUMM)	0.309	0.218	0.018	**0.848**			
Perceived ease-of-use mobile money (PEMM)	0.556	0.194	0.125	0.306	**0.863**		
Mobile money perceived usefulness (PUMM)	0.435	0.227	-0.001	0.187	0.379	**0.852**	
Personal innovativeness in mobile money (PIMM)	0.355	0.098	0.156	0.246	0.362	0.219	**0.819**

Source: own research result

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Table 5-4 Indicator item cross-loading

Items	ATMM	SEMM	TAMM	IUMM	PEMM	PUMM	PIMM
ATMM1	**0.870**	0.286	0.155	0.293	0.552	0.409	0.382
ATMM2	**0.829**	0.217	0.161	0.257	0.429	0.330	0.281
ATMM3	**0.795**	0.094	0.189	0.199	0.401	0.319	0.207
ATMM4	**0.755**	0.169	0.062	0.242	0.404	0.346	0.257
SEMM1	0.290	**0.922**	0.046	0.239	0.222	0.271	0.165
SEMM2	0.098	**0.817**	0.004	0.149	0.089	0.085	-0.016
SEMM4	0.157	**0.846**	0.006	0.134	0.128	0.143	0.010
TAMM1	0.202	-0.002	**0.935**	0.020	0.125	-0.018	0.146
TAMM2	0.071	0.039	**0.838**	-0.007	0.061	-0.032	0.106
TAMM3	0.161	0.051	**0.942**	0.023	0.130	0.031	0.158
IUMM1	0.329	0.249	0.024	**0.852**	0.294	0.207	0.236
IUMM2	0.242	0.151	0.016	**0.889**	0.252	0.143	0.203
IUMM3	0.204	0.161	-0.001	**0.765**	0.205	0.095	0.142
IUMM4	0.247	0.159	0.016	**0.882**	0.270	0.164	0.232
PEMM1	0.537	0.205	0.105	0.287	**0.885**	0.375	0.378
PEMM2	0.483	0.183	0.175	0.274	**0.910**	0.311	0.289
PEMM3	0.406	0.097	0.028	0.225	**0.789**	0.286	0.254
PUMM1	0.425	0.271	0.029	0.212	0.407	**0.879**	0.243
PUMM2	0.361	0.180	-0.007	0.110	0.288	**0.887**	0.178
PUMM3	0.306	0.092	-0.039	0.140	0.240	**0.786**	0.113
PIMM1	0.375	0.140	0.150	0.247	0.376	0.215	**0.847**
PIMM2	0.222	0.036	0.119	0.164	0.245	0.122	**0.811**
PIMM3	0.201	0.014	0.065	0.147	0.196	0.142	**0.717**
PIMM4	0.311	0.089	0.153	0.217	0.315	0.211	**0.891**

. Source: own research result

5.4.2 Structural Model and Validation

In the analysis, the following step involved evaluating the structural model and its theoretical relationships. Various factors, such as collinearity, significance, and relevance of the model paths, coefficients of determination (R^2), predictive sample reuse technique (*Q2*), and the effect size (f^2), were examined to assess the structural model. The VIF and tolerance for each predictor set were examined to verify the absence of collinearity issues, and it was determined that they were below the recommended thresholds of 5 and 0.2, respectively (J.F. Hair et al., 2017).

The R^2 values were computed for all endogenous constructs to measure the variance quantity explained in the dependent variables viewed as the predictive power of the structural model. According to Joe F. Hair et al. (2011), in the marketing field, the R^2 value of 0.25 is weak, 0.50 is moderate, and 0.75 is substantial. However, unless the adjusted R^2 is employed (for a formal explanation, see Ketchen (2013) (p. 176), this coefficient can be upward-biased in complex models where more paths are directed towards the endogenous construct. From this perspective, the coefficient of determination must be judged in the context of a research project's discipline. As shown in **Table 5-5**, all the two variables (self-efficacy and technology anxiety) explained a low variance value, i.e., 5.8% within perceived ease-of-use (R^2: PEMM=0.058). The remaining 94.2%

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can be elucidated by other variables not included in the model. The consumer attitude and personal innovativeness also explained merely 14.6% within usage intention. However, perceived ease-of-use and usefulness, are better predictors of the attitude of users since they explain the majority of variance (R^2: ATMM = 0.502); whereas self-efficacy, technology anxiety and perceived ease-of-use explain 22.3% of the variance within perceived usefulness outputs (R^2: PUMM = 0.223).

After assessing the R^2 size, the Q^2 can effectively be employed as a criterion for predictive relevance (Wynne W. Chin et al., 2008). Q^2 was then calculated using blindfolding procedures (Tenenhaus et al., 2005), and cross-validated redundancy was performed as recommended by Chin (Wynne W. Chin, 2010). A Q^2 greater than 0 implies that the model has predictive relevance, while Q^2 less than 0 implies that the model lacks predictive relevance (Fornel & Cha, 1994). **Table 5-5** reveals that the Q^2 values for attitude, usage intention, perceived ease-of-use, and usefulness were 0.241, 0.077, 0.032, and 0.110, respectively, indicating acceptable predictive relevance.

The effect size (f^2) of the variables of interest was investigated to assess the impact of each exogenous latent construct on the endogenous latent construct if deleted from the model (**Table 5-5**). According to Cohen (1988) and J.F. Hair et al. (2017), f^2 values of 0.35 indicate a strong effect, 0.15 indicate a moderate effect, and 0.02 indicate a weak effect. The f^2 values obtained from SEM analysis are presented in **Table 5-5**, which adheres to established guidelines. The results indicate that SEMM weakly affects PEMM and PUMM, while TAMM has no significant statistical effect on either PEMM or PUMM. Additionally, PEMM has a large effect on attitude and a moderate effect on PUMM, while PUMM has a moderate effect on ATMM. PIMM presents a weak effect on both ATMM and IUMM. Finally, the importance of the ATMM construct on IUMM is supported by a weak effect size value.

Overall, the results of the R^2, Q^2, and f^2 tests suggest that the findings and conclusions from this research are relatively robust.

Table 5-5 Coefficient of determination (R2), predictive sample reuse technique (Q2) and effect size (f2)

Endogenous construct	R^2	Q^2	Relationship	f^2	Decision
ATMM	0.505	0.241	PEMM→ATMM	0.327	Large
			PUMM→ATMM	0.108	Moderate
			PIMM→ATMM	0.035	Weak
IUMM	0.146	0.077	ATMM →IUMM	0.082	Weak
			PIMM →IUMM	0.024	Weak
PEMM	0.058	0.032	SEMM →PEMM	0.042	Weak
			TAMM →PEMM	0.018	No effect
PUMM	0.223	0.110	SEMM →PUMM	0.029	Weak
			TAMM →PUMM	0.005	No effect
			PEMM→PUMM	0.215	Moderate

Notes: ATMM = Attitude toward mobile money; SEMM = Mobile money self-efficacy; TAMM = Mobile money technology anxiety; IUMM = Mobile money usage intention; PEMM = Perceived ease-of-use mobile money; PUMM = Mobile money perceived usefulness; PIMM =Personal innovativeness in mobile money.

Source: own research result

PLS-SEM does not emphasize the model fit. However, it stresses maximizing the explained variance of the target constructs by considering this criterion as sufficient fit criteria (Schloderer et al., 2014). Therefore, PLS-SEM using the global goodness of fit index (GOF) is adopted as an index for the comprehensive model fit to validate whether

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the model adequately explains the empirical data (Tenenhaus et al., 2005). The GOF values range between 0 and 1, where values of 0.10 (small), 0.25 (medium), and 0.36 (large) signpost the global validation of the path model. A good model fit shows that a model is parsimonious and plausible (Henseler et al., 2016). The GOF is computed using the geometric mean value of the average communality (AVE values) and the average R^2 value(s). Based on the formula proposed by Tenenhaus et al. (2005) and the guidelines introduced by Wetzels et al. (2009) to assess the effect size of the GOF, the obtained value of GOF = 0.412 (See **Table 5-6**) led us to conclude that the goodness of fit index is large enough to support the global model validity. The GOF of the model is calculated using Equation (1) below (Tenenhaus et al., 2005).

$$GOF = \sqrt{\overline{Comunality} \times \overline{R^2}} \tag{1}$$

Table 5-6 Global goodness of fit index (GOF)

Construct	AVE	R^2
Mobile money self-efficacy (SEMM)	0.745	
Mobile money technology anxiety (TAMM)	0.821	
Perceived ease-of-use mobile money (PEMM)	0.744	0.058
Mobile money perceived usefulness (PUMM)	0.726	0.223
Attitude toward mobile money (ATMM)	0.662	0.505
Personal innovativeness in mobile money (PIMM)	0.67	
Mobile money usage intention (IUMM)	0.72	0.146
Average Values	0.727	0.233
AVE×R^2	0.169	
$GOF = \sqrt{(AVE \times R^2)}$	0.412	

Source: own research result

The next step in the analysis involved testing the corresponding theoretical relationships. Structural path analysis results are shown in **Figure 5-2**; the bold lines reveal significant relationships, whereas the dotted line shows insignificant relationships. **Table 5-7** displays the results of hypothesis testing. A t-test was adopted since all the hypotheses are well directional (J. Lu et al., 2017). Bootstrapping was performed to compute t-statistics following p-values for the path coefficients (See **Table 5-7**). Most of the hypothesized relationships regarding the direct effect were significant, except for H2b ($\beta_{TAMM \rightarrow PUMM}$ = -0.054, t = 1.08, p >0.05). The results confirm the statistical significance of nine out of the ten tested direct effects. For the indirect relationship, seven hypotheses were statistical significance amongst the eight tested indirect effects (i.e., mediating effect). H3a (β PEMM (ATMM = 0.408, t = 8.397, p < 0.001) was the most significant based on path coefficients. This implies that mobile money users rely on the perceived ease of use with low perceived usefulness during mobile money adoption. Based on H5a ($\beta_{PIMM \rightarrow ATMM}$ = 0.155, t = 4.173, p < 0.01) and H5b ($\beta_{PIMM \rightarrow IUMM}$ = 0.158, t = 3.248, p < 0.01), personal innovativeness contributes significantly to both user's attitude and intention to adopt mobile money service. As shown in **Table 5-7**, the positive and statistically significant direct effect of H5b ($\beta_{PIMM \rightarrow IUM}$ = 0.158, t = 3.248, p < 0.01) and the positive and statistically significant indirect effect of H9a ($\beta_{PIMM \rightarrow ATMM \rightarrow IUMM}$ = 0.04, t = 3.103, p < 0.01) support the complementary mediation effect (J.F. Hair et al., 2017) of the attitude of users on the relationship between personal innovativeness and intention to use. Similarly, the positive and statistically significant direct effect of H3a ($\beta_{PEMM \rightarrow}$

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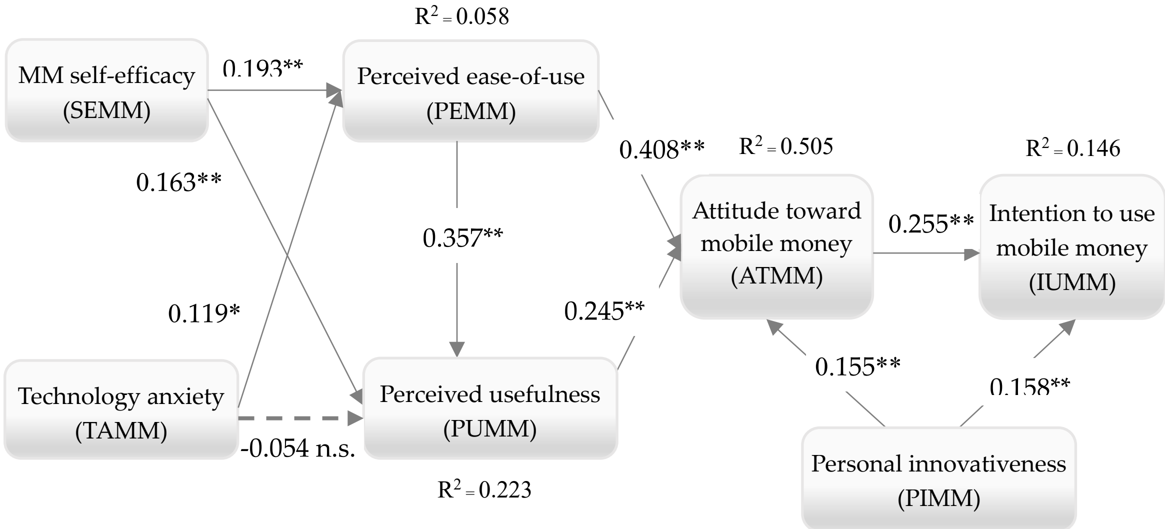
$_{ATMM}$ = 0.408, t = 8.397, p < 0.01) together with the positive and statistically significant indirect effect of H8 (β $_{PEMM \rightarrow PUMM \rightarrow ATMM}$ = 0.088, t = 4.214, p < 0.01) patronize the complementary mediation of the perceived usefulness regarding the relationship between perceived ease-of-use and attitude.

Table 5-7 Result of hypotheses testing

Hypothesis	Relationship	β	SE	t-Values	95% CI LL	95%CI UL
Direct effect						
H1a	SEMM -> PEMM	0.193	0.048	3.965**	0.109	0.267
H1b	SEMM -> PUMM	0.163	0.042	3.794**	0.09	0.231
H2a	TAMM -> PEMM	0.119	0.051	2.337*	0.031	0.201
H2b	TAMM -> PUMM	-0.054	0.046	1.08	-0.131	0.02
H3a	PEMM -> ATMM	0.408	0.048	8.397**	0.33	0.487
H3b	PEMM -> PUMM	0.357	0.049	7.187**	0.277	0.435
H4	PUMM -> ATMM	0.245	0.05	4.899**	0.158	0.327
H5a	PIMM -> ATMM	0.155	0.037	4.173**	0.096	0.214
H5b	PIMM -> IUMM	0.158	0.048	3.248**	0.078	0.242
H6	ATMM -> IUMM	0.255	0.046	5.475**	0.174	0.326
Indirect Effect						
H7a	SEMM -> PEMM -> ATMM	0.078	0.023	3.428**	0.042	0.116
H7c	TAMM -> PEMM -> ATMM	0.049	0.021	2.254**	0.014	0.083
H7b	SEMM -> PUMM -> ATMM	0.041	0.013	2.935**	0.02	0.063
H7d	TAMM -> PUMM -> ATMM	-0.013	0.011	1.099	-0.028	0.008
H8	PEMM -> PUMM -> ATMM	0.088	0.021	4.214**	0.057	0.126
H9c	PEMM -> ATMM -> IUMM	0.104	0.023	4.502**	0.068	0.143
H9b	PUMM -> ATMM -> IUMM	0.064	0.018	3.497**	0.037	0.097
H9a	PIMM -> ATMM -> IUMM	0.04	0.013	3.103**	0.02	0.062

Notes: ** P < 0.01, *P < 0.05; SEMM = Mobile money self-efficacy; TAMM = Mobile money technology anxiety; PEMM = Perceived ease-of-use mobile money; PUMM = Mobile money perceived usefulness; PIMM =Personal innovativeness in mobile money; ATMM = Attitude toward mobile money; IUMM = Mobile money usage intention.



Notes: ** P<0.01, *P<0.05, n.s.= No statistically significant effect

Figure 5-2 SEM path analysis results
Source: own research result

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5.5 Artificial Neural Networks (ANNs) and Sensitivity Analysis

Many parametric statistical techniques necessitate a great statistical background, whereas artificial neural networks (ANNs) are non-parametric models (Azizi et al., 2019). ANNs are the most effective models among intelligent methods (S. O. Haykin, 2008). ANNs techniques refer to a massively parallel distributed processor comprising simple processing units, which have a neural tendency to store experimental knowledge and make it available for use (Baldi & Hornik, 1995). They are very comparable to the way the biological neural networks in the human brain such that knowledge is collected through the learning or training process and stored by ‘‘interneuron connection strengths recognized as synaptic weights’’. They use a massive interconnection of simple computing units termed neurons or nodes in input, hidden, and output layers with connection strengths called synaptic weights that are adjusted via an iterative process (L.-Y. Leong et al., 2013). The interconnection pattern between these neurons in ANN represents the network architecture. Each input has a connected weighted *(w)*, attributed based on its relative importance to other inputs. The node uses a function *f* defined as a weighted sum of its inputs based on the following formula:

$$Y = f(w_1 x_1 + w_1 x_1 + b) \tag{2}$$

Where w_1 and w_2 are weighted, x_1 and x_2 are input, *b* represents bias, and Y is output. **Figure 5-3** represents the general network architecture for a single-layer perceptron.

One particularity of ANN is to deal equally with a linear and non-linear relationship, requiring any distribution assumptions such as normality, linearity, or homoscedasticity compared to SEM (L.-Y. Leong et al., 2013). Hence, the function *f* is non-linear, a so-called activation function.

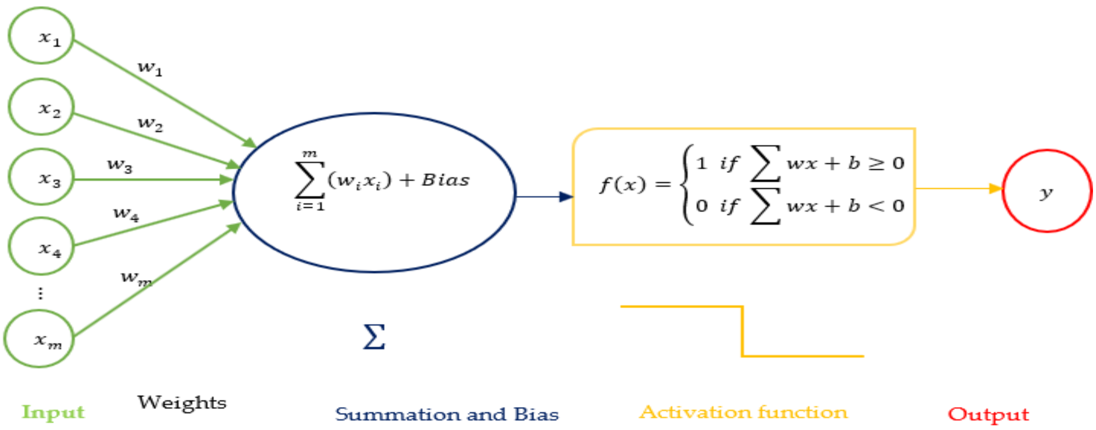

Figure 5-3 Network architecture for a single-layer perceptron procedure
Source: own elaboration

Selecting a proper activation function remains important because it can affect how the input data should be set up and the output format would be generated.

There are three commonly used activation functions, i.e., sigmoid, hyperbolic tangent (Tanh), and rectified linear unit (ReLU), as presented in the formula below. The Sigmoid function is an activation function having an output bound between [0, 1], while the Tanh function has an output range of [−1, 1]. Relu function refers to the activation function returning the max (0, x). Although the output layer can have any activation functions, Sigmoid is the widely used activation function for the output layer in the information technology context (Sujeet Kumar Sharma, 2019). Sigmoid function and their combinations fundamentally work better in the context of classifiers and sometimes

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prefer when the researcher expects an output or intermediate layer of the net to represent the probability of an event. Each neuron's normalizing output can also be assessed based on the sigmoid's output range.

$$\mathrm{Sigmoid}(x) = \frac{1}{1+e^{-x}} \tag{3}$$

$$\mathrm{Tanh}(x) = \frac{2}{1+e^{-2x}} - 1 \tag{4}$$

$$\mathrm{ReLU}(x) = \max(0, x) \tag{5}$$

A feedforward backpropagation (FFBP) neural network is an ANN that employs a supervised learning procedure with a feed-forward algorithm for prediction. It is viewed as advanced multiple regression analysis (MRA) or SEM able to deal with complex and non-linear relationships.

In this study, the extensive neural network model –multilayer perceptron (MLP) with the FFBP training algorithm– was applied (A. Y. L. Chong, 2013) (Yadav et al., 2016) in SPSS 21 using the sigmoid activation function for hidden and output layers (Ooi & Tan, 2016). This sigmoid function will converge to one for large positive numbers and 0.5 for zero, and very close to zero for large negative numbers. Therefore, it allows transitions between the low and high output of the neuron. The output is subject to activation, which relies on the input values and their corresponding weights. The number of neurons in the input layer is equivalent to the number of predictor constructs. Similarly, the number of neurons in the output layer equals the number of dependent variables, i.e., predicted constructs, and the problem scheme determines all.

Over-fitting is a major issue in the predictive modeling approach. A ten-fold cross-validation technique was performed to avoid over-fitting, with 90% of the sample used for training and the remaining 10% of the hold-out data for testing purposes (Ooi & Tan, 2016). Determining exactly hidden nodes is considered one of the most challenging in the literature. Wang & Elhag (2007) suggested a range of one to 10 hidden nodes in the neural network model. The number of hidden units was engendered automatically, and the root-mean-square-error (RMSE) values were computed together with the normalized importance in the sensitivity analysis.

The accuracy of the network models is assessed by RMSE (Yadav et al., 2016), which is computed as the difference between actual and predicted values of the dependent constructs, i.e., consumers' intention to use mobile-based money services. The summary of RMSE values for all four ANN models is provided in **Table 5-8**. The RMSE values achieved through all four neural network models for training and testing data points are minimal. Hence, the results are relatively accurate (Francisco Liébana-Cabanillas et al., 2017) (Sujeet Kumar Sharma, 2019). The number of non-zero synaptic weights linked to the relevant hidden units is used to validate the relevance of the variables (See **Table 5-9**). Therefore, it can be concluded that all factors are significant in predicting the dependent variable. The normalized or relative importance values were computed as the ratio of the relative importance of each variable with its largest importance and expressed in percentage form (Francisco Liébana-Cabanillas et al., 2017). Only significant linear factors obtained via the SEM technique were regarded as the input units of the ANN models. From **Table 5-10**, the sensitivity analysis performance was then computed by averaging the importance of the input variables in predicting the output for the ten networks (A. Y. L. Chong, 2013). Therefore, the causal relationships' relative strengths were assessed based on the normalized importance from the sensitivity analysis (G. W. H. Tan et al., 2014). SEMM was the critical determinant in predicting PEMM, followed

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by TAMM in model A. In model B, PEMM is the most prominent predictor for PUMM, followed by SEMM. For model C, the order of importance towards ATMM in descending order is PEMM, followed by PUMM and PIMM. It is worth noting that ATMM had the highest predictive ability for IUMM, followed by PIMM.

It is remarkable that in contrast to structural models, which can only identify linear relationships, the ANN models (shown in **Figure 5-4**) are capable of learning complex linear and non-linear relationships among decision variables, as highlighted by Sujeet Kumar Sharma (2019).

Table 5-8 RMSE values of ten artificial neural networks

	Model: A		Model: B		Model: C		Model: D	
Network	Input neuron: SEMM, TAMM		Input neuron: SEMM, PEMM		Input neuron: PEMM, PUMM, PIMM		Input neuron: PIMM, ATMM	
	Output neuron: PEMM		Output neuron: PUMM		Output neuron: ATMM		Output neuron: IUMM	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing
ANN1	0.1369	0.0495	0.1387	0.0375	0.0969	0.0367	0.1472	0.0579
ANN2	0.1390	0.0511	0.1321	0.0555	0.0972	0.0369	0.1498	0.0505
ANN3	0.1358	0.0521	0.1425	0.0306	0.1033	0.0254	0.1490	0.0554
ANN4	0.1395	0.0432	0.1413	0.0479	0.1088	0.0405	0.1505	0.0539
ANN5	0.1396	0.0415	0.1364	0.0441	0.1037	0.0342	0.1510	0.0516
ANN6	0.1371	0.0489	0.1379	0.0379	0.1004	0.0318	0.1543	0.0424
ANN7	0.1385	0.0472	0.1387	0.0355	0.1025	0.0234	0.1499	0.0524
ANN8	0.1400	0.0525	0.1430	0.0427	0.0977	0.0385	0.1485	0.0554
ANN9	0.1383	0.0533	0.1353	0.0459	0.1033	0.0239	0.1499	0.0522
ANN10	0.1415	0.0515	0.1351	0.0464	0.1021	0.0365	0.1522	0.0476
Mean RMSE	0.1386	0.0491	0.1381	0.0424	0.1016	0.0328	0.1502	0.0519
Standard deviation	0.0017	0.0040	0.0035	0.0072	0.0037	0.0064	0.0020	0.0044

Notes: SEMM = Mobile money self-efficacy; TAMM = Mobile money technology anxiety; PEMM = Perceived ease-of-use mobile money; PUMM = Mobile money perceived usefulness; PIMM =Personal innovativeness in mobile money; ATMM = Attitude toward mobile money; IUMM = Mobile money usage intention.

Source: own research result

Table 5-9 Relevance of variables based on non-zero synaptic weight with hidden neurons

Model	Predictor variable	Artificial neural network									
		ANN1	ANN2	ANN3	ANN4	ANN5	ANN6	ANN7	ANN8	ANN9	ANN10
A	SEMM	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	TAMM	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
B	SEMM	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	PEMM	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
C	PEMM	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	PUMM	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	PIMM	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
D	PIMM	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	ATMM	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Dependent variable = IUMM (Mobile money usage intention); SEMM = Mobile money self-efficacy; TAMM = Mobile money technology anxiety; PEMM = Perceived ease-of-use mobile money; PUMM = Mobile money perceived usefulness; PIMM = Personal innovativeness in mobile money; ATMM = Attitude toward mobile money; ✓ indicates at least one non-zero synaptic weight was connected to the hidden neurons

Source: own elaboration

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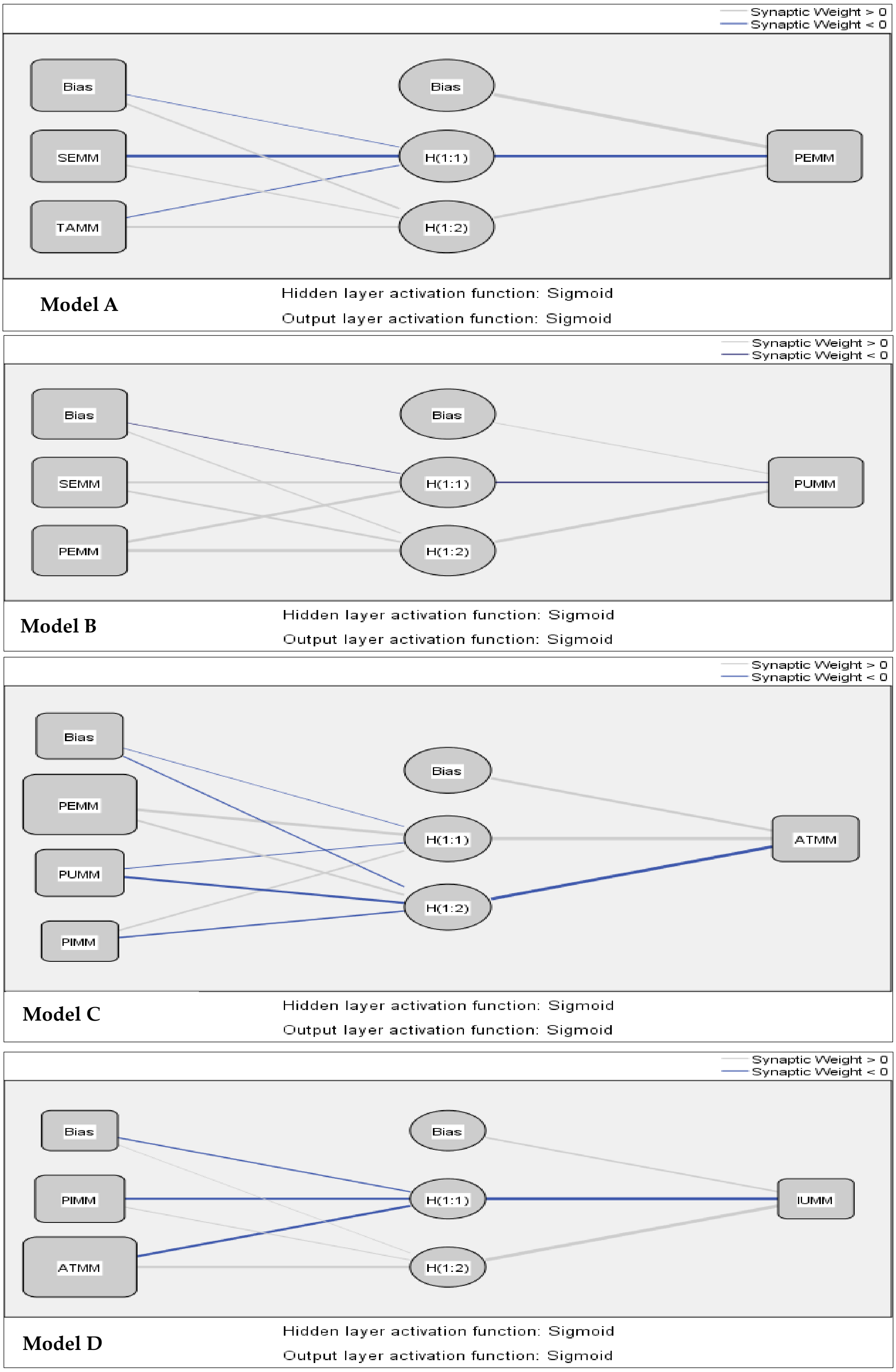

Figure 5-4 Artificial neural network used in this study

Source: own research result

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Table 5-10 Neural network sensitivity analysis

Network	Model A		Model B		Model C			Model D	
	Output neuron: PEMM		Output neuron: PUMM		Output neuron: ATMM			Output neuron: IUMM	
	Relative importance		Relative importance		Relative importance			Relative importance	
	SEMM	TAMM	SEMM	PEMM	PEMM	PUMM	PIMM	PIMM	ATMM
ANN1	0.562	0.438	0.334	0.666	0.495	0.310	0.194	0.405	0.595
ANN2	0.612	0.388	0.321	0.679	0.528	0.308	0.165	0.368	0.632
ANN3	0.566	0.434	0.334	0.666	0.541	0.239	0.220	0.442	0.558
ANN4	0.548	0.452	0.100	0.900	0.419	0.255	0.326	0.517	0.483
ANN5	0.520	0.480	0.299	0.701	0.422	0.270	0.308	0.531	0.469
ANN6	0.537	0.463	0.221	0.779	0.617	0.184	0.199	0.500	0.500
ANN7	0.630	0.370	0.328	0.672	0.602	0.277	0.120	0.478	0.522
ANN8	0.831	0.169	0.594	0.406	0.390	0.278	0.332	0.286	0.714
ANN9	0.660	0.340	0.220	0.780	0.568	0.224	0.208	0.389	0.611
ANN10	0.645	0.355	0.272	0.728	0.402	0.303	0.295	0.503	0.497
Average relative importance	0.611	0.389	0.302	0.698	0.498	0.265	0.237	0.442	0.558
Normalized importance (%)	100.0	63.6	43.3	100.0	100.0	53.1	47.5	79.2	100.0

Notes: SEMM = Mobile money self-efficacy; TAMM = Mobile money technology anxiety; PEMM = Perceived ease-of-use mobile money; PUMM = Mobile money perceived usefulness; PIMM =Personal innovativeness in mobile money; ATMM = Attitude toward mobile money; IUMM = Mobile money usage intention.

Source: author's computation

5.6 Discussion

Numerous studies have highlighted the importance of evaluating the primary factors that influence the adoption of new technologies. The present study examined the factors affecting the adoption and sustainability of mobile money in the context of Togo. These factors were based on the TAM framework, which was extended to include variables like self-efficacy, technology anxiety, and personal innovativeness, all of which have been identified and tested in previous studies.

A hybrid structural equation modeling–artificial neural networks approach (SEM-ANN) was used to test the proposed hypotheses based on these factors. The results confirmed most of the hypotheses, with only two paths linking new technology anxiety (TAMM) and perceived usefulness (PUMM) found to be statistically insignificant. Overall, the analytical findings suggest that the research model used in this study is satisfactory. The subsequent subsections provide a more detailed discussion of the results.

5.6.1 Relationships between SEMM, TAMM, and PEMM.

Self-efficacy in mobile money service (SEMM) has the highest normalized importance and showed a significant relationship with the perceived ease-of-using (PEMM) mobile money in the present study. This finding supports prior research on mobile payment acceptance (A. A. Bailey et al., 2017) (He et al., 2018). Particularly, the construct of SEMM has long been associated with perceived ease of use in the IS adoption literature (Polites & Karahanna, 2018). Altogether, it is rational to argue that self-efficacy will lead a consumer to believe his or her ability or to see the procedure of making mobile money easy to use, therefore carrying out successful mobile money adoption. The findings in this

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study also show that TAMM, with 63.6% normalized importance, is positively related to the ease of using mobile money. Therefore, customers who are even anxious about using technology may, to some extent, perceive mobile money as easy to use. When the user's anxiety about using mobile money is mitigated, the system's perceived ease of use will be lower. This result contradicts past research that defines anxiety, particularly computer anxiety, as the propensity of a person to experience uneasiness over his or her impending use of a computer (Howard & Smith, 2002).

5.6.2 Relationships between SEMM, PEMM, TAMM, and PUMM

The path coefficient between SEMM and PUMM is 0.163 ($p < 0.01$), a significant positive correlation with the highest normalized importance. This result indicates that when users perceived their ability to master the use of mobile money transfers, their effectiveness increased the usefulness or utility of mobile money. Concerning the self-efficacy effect on perceived usefulness, this research's finding is compatible with existing studies' findings (Ariff et al., 2012). The path coefficient between PEMM and PUMM with 0.357 ($P<0.01$) was found to be positive and significant, which confirms the results of earlier studies (Upadhyay & Jahanyan, 2016) (Van der Heijden, 2003) (J. Lee et al., 2019). The degree of usefulness of technology is viewed based on how much users perceive the ease of use. This result is in line with the work of Muñoz-Leiva et al. (2017). With other things being equal, users view technology as more beneficial when it is free of effort concerning the effort of expectancy. This finding contradicts the research conducted by Chauhan (2015) on the adoption of mobile money amongst the poor citizens of India. There is no empirical evidence to accept H2b ($\beta = -0.054$; $p > 0.05$), thus failing to demonstrate the importance of new technology anxiety through the usefulness of using mobile money services. This result opposes the previous study on mobile payment in the USA (A. A. Bailey et al., 2017).

5.6.3 Relationships between PEMM, PUMM, and PIMM on ATMM

PEMM is the most significant factor in determining ATMM and has the highest normalized value, followed by PUMM and PIMM. A probable explanation is that mobile money services remain a relatively new phenomenon in e-business, and most mobile financial companies are still in the early diffusion stage. When a technology has newly emerged, users probably delay espousing it due to their concern with the efforts involved in using the technology and its intricacy. Similarly, users will be unwilling to welcome the novel technology if they do not know how it works. To some extent, this result is partially supported by earlier empirical studies in mobile banking (Muñoz-Leiva et al., 2017). Regarding the impact of perceived usefulness, empirical evidence is found to accept H4 ($\beta=0.245$ $P<0.01$), showing the importance of usefulness through the attitude based on the proposed mobile money services as it is consistent with the existing TAM research (Muñoz-Leiva et al., 2017) (S. Y. Hung et al., 2013). The perception of usefulness has commonly been regarded as a perceived relative advantage in many studies. Rogers (2003b) explains that relative advantage refers to how a product is perceived as superior to its predecessor. The current study's findings indicate that this factor is relevant for mobile money services, which are considered innovative in mobile financial services. The usefulness of mobile money is closely linked to its benefits, such as the ability to transfer money quickly and securely at a low cost. Therefore, if individuals are made aware of the usefulness of mobile money, it will encourage its adoption, as significance leads to momentum, according to K. Kelly (1997). The service providers should ensure that there should be conscious and focused efforts on spreading

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the message of the usefulness of mobile money to its potential users through a focused marketing strategy. Regarding the fundamental constructs of TAM, such as perceived ease-of-use and perceived usefulness, it was detected in the SEM outcome that these two factors impact attitudes significantly towards the application of mobile money. The results indicate that in Togo, users of mobile money services are not solely drawn to their usefulness but also value the ease of their operation. Furthermore, the innovativeness of the services finds to be one of the factors that influence the usage of mobile money, which is supported by earlier results in the context of a web survey (J. Fang et al., 2009). For achieving optimal usefulness and ease of use for mobile money services, it is recommended that service providers focus on integrating features that users find valuable and are easy to apply, particularly given that the majority of respondents have attained at most an A-level education (Baccalaureate) or less. Potential respondents with high personal technology innovativeness are expected to be more willing to develop the attitude to use mobile money than those with low personal innovativeness if all things are equal. The most likely explanation of this empirical evidence is the low maturity level of users towards mobile money in this developing country.

5.6.4 Relationships between PIMM and ATMM on IUMM

PIMM with normalized importance of 79.2% was found to have a significant relationship in predicting IUMM. The result corroborates with research done in the context of mobile learning (Y. Liu et al., 2010) and contradicts J. Lu et al. (2005) and A. Y.-L. Chong (2013) studies. Personal innovativeness plays a central role in predicting intentions for the usage of technological innovation (Heijden, 2004). Most individuals with greater personal innovativeness have more courage, higher personality principles, and social-economic status. Hence when undertaking any technology adoption, they are likely to develop positive feelings towards intention as opposed to individuals with lower personal innovativeness. ATMM shows a significant influence in predicting the UIMM and is consistent with the prior study (A. A. Bailey et al., 2017). According to the finding of this research, once the users develop a good attitude regarding using mobile money, the behavioral intention to use it will follow. The result justifies the inclusion of attitude as a variable in mobile money adoption and the sustainable mobile financial industry.

5.7 Conclusion and Implications

Mobile money transfer is one of the latest innovative financial applications of mobile technologies. Due to the lower acceptance of mobile money in Togo, this research grasped the importance of understanding and assessing key determinants affecting mobile money acceptance. Therefore, the research aims to study those beliefs and behavioral variables that impact the acceptance and sustainability of mobile money applications from the developing country perspective and offer conclusions beyond mere descriptive analysis.

Togolese mobile financial service providers may develop appropriate business policies and strategies for mobile money transfer systems, enhancing overall business performance. To reach this objective, the traditional TAM model has been used, to which relevant constructs were added in adopting an innovation, such as self-efficacy, new technology anxiety, and personal innovativeness allied with the proposed methodological application. A survey was conducted among the users and potential users of mobile-based money services to analyze the proposed theoretical model. The proposed model employed a two-stage SEM-ANN approach– SEM for testing possible relationships and ANN for predicting the determinants of mobile money. The predictive analytical approach of the

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neural network was employed to assess the data, and the outputs from the data were utilized to compare with the ones from structural equation modeling analysis. Such an integrated methodology provides a rigorous and comprehensive reference for future research on mobile money transfer from the perspectives of developing countries.

Moreover, this research reveals the relevance of the two-stage approach integrating SEM and ANN techniques to enhance the assessment of technology adoption models for decisions makers. By comparing the results of the SEM and the ANN analyses, the major difference lies in the strength of the effect of the two constructs relating to innate personal ability and personality traits. The ANN analysis increases the relative importance of self-efficacy in the ease of using a mobile money transfer. Similarly, the relative importance of personal innovativeness has been improved regarding its effect on users' attitudes and intentions to use mobile money with ANN analysis. The results reveal that ANNs are better than SEM in learning, predicting, and clarifying various factors influencing mobile money adoption. However, SEM supports the causal analysis (the reliability and validity of the measurements and path analysis), which is limited in ANN application. Therefore, a multi-analysis technique such as the integrated approach (SEM-ANN) contributes more to sharpening the understanding of model variables' effect than using a sole technique.

From a different angle, the outcomes of this research have immense practical and managerial implications. This study can provide useful insights to the decision makers of telecommunication service providers, mobile money app developers, and mobile money service providers to enhance and maintain their customer base. First, the government of several emerging economies has been making efforts to achieve greater financial inclusion by using technology (Aggarwal et al., 2010). Recently, African Development Bank (AfDB), in collaboration with the government of Togo, offered subsidies to farmers through e-wallets provided by mobile network operators Moov and Togocel in patronizing the digitization project of the agriculture transformation agenda (Aggarwal et al., 2010). Grounded on the World Bank/AfDB report, mobile financial services (MFS) significantly positively influence the macroeconomic development of some West African Nations, and even the percentage of effect could reach a double-digit. Based on the proportion of GDP, the most significant beneficiaries are Togo (10.7%) and Cape Verde (9.4%) (Ratha et al., 2011). Islam et al. (2018) reported the significant benefits of mobile money on a firm investment in three East African economies and encouraged using such services in other developing countries.

Given the importance of financial inclusion and sustainable development, mobile money transfer services might go a long way in solving the concerns of the non-existent banking network. Banks have been reluctant to open branches in far-reaching zones because of security and viability issues. Thus, mobile money transfers can effectively fill that need and be an effective instrument for greater financial inclusion (Reeves & Sabharwal, 2013). This study reveals that the perceived usefulness of mobile money services impacts the consumer's attitude regarding the decision to adopt this technology, including its ease of operations. The developers of mobile money apps must focus on developing user-centric apps to create awareness of usefulness together with ease in operations of users in their view. Then, in turn, should lead to increased financial transactions conducted on mobile devices. It is important to stress the influential role of personal innovativeness on the users' attitude and intention to use mobile money. For the scholars' conceptualization of personal innovativeness, a person is called innovative if he or she is early to adopt an innovation (Ritu Agarwal & Prasa, 1998) (H. Xu & Gupta, 2009). Therefore, personal innovativeness acts as an enabler of user behavior, and

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company providers need to stimulate this factor to facilitate the usage of mobile money services. This signposts that for the usage of such services, users are seeking not only basic functionality but also innovations. Service providers may ponder directing some of their advertising campaigns to the segment of more innovative uses. As per Moore & Benbasat (1991) suggestion, innovators offer companies great feedback early in the design cycle and start building a supporter who will impact buyers. Since gathering big data on consumer behavior and habits through mobile phone sensors is now possible, an artificial intelligence approach could be utilized to profile each consumer and offer personalized service that the customer would find innovative and valuable. For Midgley (1978), innovators regarded as early adopters are more likely to be opinion leaders, and the messages these innovators address to others stimulate the interpersonal predisposed adoption process of light users or non-users. It will positively impact the increase in mobile-based money adoption rate.

5.8 Limitation and Future Research

This research presents a series of limitations that would pave the way for future study. This study did not consider moderating variables, such as individual customers' experiences with mobile money in other mobile financial services, age, and gender proposed by Venkatesh & Bala (2008), the impacts of which could be empirically tested in future studies. Furthermore, the model is cross-sectional in that it measures perceptions, attitudes, and intentions at a single point in time. However, perceptions alter over time as individuals gain experience (Mathieson, 1991). With our cross-sectional data, we also only took a snapshot of this model. Due to the limitations, a stricter test of our argument could lead researchers and practitioners to be interested in predicting mobile money usage over time by employing a longitudinal study. In the future, by conducting a longitudinal study, the research model can be examined at various intervals and compared, providing a deeper understanding of the mobile money adoption phenomenon.

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Chapter 6 Assessing Perceived Risk in Mobile Money Adoption under COVID-19: A Combined SEM-Artificial Neural Network Techniques

6.1 Introduction

The world has been facing an unprecedented coronavirus health crisis for over a year. Throughout history, the world has experienced pandemics through the great plague and the 1918 influenza pandemic (Taubenberger et al., 2019). However, the COVID-19 pandemic remains one-of-a-kind due to at least two motives. First, more than three billion were told to stay home worldwide over the virus in March 2020 (Beaunoyer et al., 2020); its magnitude and impacts are unparalleled. In the middle of 2020, several nations that initially imposed strict lockdown measures lifted them or are doing so. However, policy approaches differ considerably (López & Rodó, 2020). The second deadly epidemic wave during the 1918 influenza pandemic, apparently caused by strain mutations (Martini et al., 2019), has also motivated a vigorous debate on whether actions should incorporate this option. Second, there is a significant difference between the period of compulsory isolation we collectively live in and historical quarantines: the overpowering presence of technology (Guitton, 2020). Governments and supra-national bodies such as the World Health Organization (WHO) convey their messages and recommendations as preferred and privileged channels through online technologies. More importantly, technology is becoming central to maintaining active social interactions. Thus, the COVID-19 pandemic crisis intensifies the importance of information technology (IT) evidence and digital transformation, such as mobile financial services (MFS).

Considering the evolution of information technology communication (ICT), banking systems adopt technology to patronize bank services efficiently. The mobile money application (MMA) remains a portable technology-based app that has become a considerable payment mode today. It is viewed as a bank subsidiary, with its services used to access and complete financial transactions. According to Gichuki & Mulu-Mutuku (2018), cell phone coverage and usage have exponentially grown. Moreover, the Statista report in 2021 revealed the global LTE (long-term evolution) population coverage of around 83 percent, while the newest mobile technology (i.e., 5G) covered approximately 15 percent in 2020. Therefore, MMA services are a potential solution to support financial transactions (Tchouassi, 2012). The number of cell phone subscriptions in Africa increased speedily from a 22.9% share of the population in 2005 to 89.4% in 2013 (Chaix & Torre, 2015). However, less than 25% of the adult population had a bank account in the same period (Demirgüç-Kunt & Klapper, 2013). Thus, an increase in mobile telephony users and Internet penetration seems to have a high potential for opening up access to financial services for unbanked people in developing countries (Assadi & Cudi, 2011) and massive growth in the adoption and use of the MMA services community. Given the current global crisis, it would also be sensible to indicate that currency notes have been conditioned to be the carrier of microorganisms and deadly viruses (Alemu, 2014). Recently, currency notes were emphasized to factor in the spreading coronavirus (COVID-19) to the point that banknotes circulated in Europe and Asia were quarantined for some days (Lucre, 2020). Many business operators have also decided not to accept customer banknotes (Lucre, 2020). The adoption of e-money becomes much more practical and indeed safer than physical currency; therefore, enough to encourage people

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to switch to e-money, mainly in emerging market societies. Despite IT advancements, many questions remain about adopting mobile money services (MMS).

In the context of Togo, mobile money users commonly transfer money to a relative. Equally, users adopt services to pay service bills such as electricity, water, telephone, and TV subscription and pay in supermarkets and restaurants (see African Development Bank report 2015) (Assadi & Cudi, 2011). As reported by the central bank of West African States (i.e., BCEAO in French) in 2016, the banking rate in Togo was less than 15%. In contrast, approximately 67% of the populace subscribed to mobile telephony in 2014 (Couchoro, 2016). Furthermore, in the West Africa Economic and Monetary Union (WAEMU) zone, by the end of 2019, mobile money recorded 76.97 million account openings and 2.633 billion transaction volume at about 28.738 billion FCFA value transactions a variation of 37.9% between 2018/2019. Togo's share was lower than 6% of account openings, volume, and the aggregate value of transactions (BCEAO, 2020). FCFA is the franc of the African Financial Community (Benin, Burkina Faso, Côte d'Ivoire, Guinea-Bissau, Mali, Niger, Senegal, and Togo), 1 dollar US is approximately 545 FCFA. From the overview of MFS data, Togo is lagging in adopting mobile money in the WAEMU zone. As a result, mobile money is expected to impact the access rate to financial services substantially. On the ground, this is far from the case.

Mobile money provides numerous benefits, yet, it has been demonstrated to be a double-edged sword. For instance, it may offer many advantages, such as faster transaction speed, 24-hour availability, and reduced operational cost. Still, it poses various risks and threats, such as malware, spyware, phishing, spoofing, and password-sniffing (de Kerviler et al., 2016) (Narteh et al., 2017). In Togo, with mobile money services (MMS) at the developing stage, customers' motives for resisting such services could be attributed to their perceived risk of conducting online transactions (Gbongli et al., 2017). As a result, emerging economies must accept and acknowledge the risk to grow and flourish (S. K. Singh & Gaur, 2018). The concept of perceived risk has been explored in several kinds of literature (Ming Chi Lee, 2009) (Martins et al., 2014) (Roy et al., 2017) (Abdul-Hamid et al., 2019) (Susanto et al., 2020). However, not many studies have focused on the specific context of predicting and ranking risk directly through the aggregate perceived risk using a combined methodology. Studies relating to the perceived risk in customer intention to adopt and use e-money services have not been of much concern among researchers, especially in the perspective of a developing economy. Previous studies have considered the perceived risk as one of the inhibitors in digital money adoption, and it has yet to be conceptualized and examined on a multidimensional scale (Koenig-Lewis et al., 2015). Therefore, it is necessary to study the resistance factors in using MMS to raise its adoption rate among consumers. Several researchers have also highlighted that different contextual aspects must be integrated to assess customers' behavior regarding technology acceptance and use fundamentally (Hashim et al., 2015) (Venkatesh et al., 2012a). This model considers the customer-perceived dimensions outlined by Featherman & Pavlou (2003) to shed some light on the components that hinder e-money acceptance.

The importance of this research is twofold. First, this research can address the extant mobile money literature gap by offering empirical evidence and theoretical support regarding MMS inhibitors during the pandemic. Thus, this study herein develops and empirically validates a research framework that can examine the relationship between the multidimensional perceived risk (i.e., privacy, time, security, and monetary risk) and perceived overall risk (POR) in a model. It also presents the relation between POR and

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consumers' behavioral intention (BI) towards MMS adoption. Second, we examine a two-stage methodology, i.e., structural equation modeling (SEM) - artificial neural network (ANN), to develop and test a model that can better predict consumers' POR to use innovative technology such as MMS. Therefore, the study uses an SEM-ANN approach in capturing linear-nonlinear and non-compensatory relations between the exogenous and endogenous variables. With this methodology, the complexity of consumer decision-making on resistance to mobile money service is better explained.

The significance of the contribution revealed that perceived privacy risk was singled out as the most critical influence on the POR, in which the latter negatively impacted the behavioral intention to use MMS. Therefore, a new connection to the determinant of overall risk and intention to use MMS is uncovered. This result suggests new ideas which are essential for policy formulation. MMS companies' providers should formulate strategies that most effectively reduce an individual's concerns toward these services. This can be done by integrating advanced data management techniques, such as data encryption platforms, to guarantee security in financial transactions and promote citizens' trust since privacy seems superfluous when security is present. Furthermore, the integrated SEM-ANN (capturing linear-nonlinear and non-compensatory relations between variables) improves the accuracy of existing alternatives, so a particular open question is resolved. Therefore, the study extends existing methodologies and research practices such that using ANN is another step from traditional linear regression techniques.

The paper is outlined in various sections. Its starts with an introduction followed by a review of existing studies. Then, we propose the hypothesis and the research model. The following section details the methodology used, while section five presents the data analysis with research results. Lastly, we conclude the study with implications, limitations, and suggestions for future research.

6.2 Literature Review and Theoretical Framework

6.2.1 Promoting Mobile Money Usage to Curb the Spread of the COVID-19

Since starting the COVID-19 pandemic, digital spaces have been the central channel government and official agencies, including the World Health Organization (WHO), have employed to disseminate information regarding the measures people must implement to avoid getting contaminated and contaminated others (C. Lee et al., 2008). The demand for accessing and understanding online information and following recommendations are crucial as far as the capacity of individuals to take protective actions is required. With the number of COVID-19 cases that upsurge, many people are choosing cashless payments to prevent direct contact and potential hygiene concerns due to banknotes, which may facilitate the spread of COVID-19. This situation increases the call for digital payments, predominantly mobile money – a service in which the mobile phone is employed to access financial services – to those who have not considered this transaction method.

Mobile money has various features that can support undisrupted financial transactions in the present pandemic. The World Health Organization has enumerated several ways to prevent the spread of the COVID-19 virus. Some of these methods have led people to avoid direct contact with others while driving communities to use digital payment options as an alternative for day-to-day transactions. Moreover, many countries have imposed "lockdowns," leading various banks, money exchange providers, and retail businesses to reduce their hours of operation or even close altogether. Therefore, mobile money has turned out to be an attractive option for making payments. Several governments and retail businesses have also discouraged using physical cash for transactions. Conversely, mobile

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money enables account holders to transfer e-money and conduct other financial transactions with minimal physical contact, helping alleviate the spread of the virus.

Studies have shown that notes and coins can spread bacteria and germs, facilitating the spread of the COVID-19 virus. However, digital imbalances continue to increase vulnerability to the COVID-19 virus and crisis concerns (Beaunoyer et al., 2020). Decreasing or ideally eliminating physical cash transactions and creating digital money opportunities could help stop the spread of bacteria and germs. According to a World Economic Forum publication, moving away from cash is vital in emerging markets (Reuters Staff, 2020). Africans are urged to switch to digital payment alternatives to reduce the coronavirus risks of exchanging money in cash. From this end, Kenya's government has explored ways of expanding mobile money usage to curb the risk of spreading the virus by physically handling cash. Similar actions were undertaken to reduce the risk of COVID-19 transmission through mobile money in Ghana, Nigeria, and Uganda. It has been reported that mobile money service (MMS) usage during the pandemic has grown by 6% globally, with West Africa experiencing the most significant upsurge in MMS usage (Reuters Staff, 2020).

Two distinct phenomena related to digital money have contributed to fighting during the pandemic. One part is that banknotes and coins were assumed to be carrying the virus, and digital payment was desired for the "dirty money" (Sangster, 2020) (S. M. Kelly, 2020). Online delivery services were urging customers to make payments using digital payment systems such as credit/debit cards or mobile payments, which were enforced or mandated by the government in several parts of the world, such as India (N. Kapoor, 2020). Lastly, during the lockdown, there was a loss of jobs. Various governments, including Togo, offered cash transfer programs to assist vulnerable households via payment apps and digital payment modes. These are a convenient approach to fund transfer from donors to recipients, as seen in earlier crisis relief situations (Pollach et al., 2005). Grounded in earlier crisis and disaster events, where the mobility of citizens was restrained, many MMS providers (e.g., Vodafone in Afghanistan and Safaricom in Kenya) have offered a fast fund transfer of remittances from migrants to their homes and relief aid from the government to victims (Jenny C. Aker et al., 2016) (Wachanga, 2015). A similar situation has been observed during the COVID-19 pandemic, requiring scholars for future studies (De' et al., 2020). Despite the disruption in the global economy, it is crucial to note that mobile money has proven valuable in enabling safe and efficient financial transactions throughout the pandemic.

6.2.2 Perception of Risk in Mobile Money Services

Bauer was the first to introduce the concept of perceived risk into marketing literature (Bauer, 1960). Before making any purchasing decision, the risk is considered a vital concept to assess the uncertainties or unpleasant effects of searching for and picking items or services (Kesharwani & Singh Bisht, 2012). Several studies have focused on risk perception concerns (Curran & Meuter, 2007) (Flavián et al., 2006). Due to the intrinsically risky environment of the internet, intangibility, lack of control, anonymity, security, and privacy protection characterized in the mobile financial services (MFS) area, as well as the absence of human interaction (A. P. Pavlou, 2003) (Alalwan et al., 2017) (Featherman & Pavlou, 2003) (Martins et al., 2014), the possibility of unfavorable results remains somewhat high in the context of online business.

Perceived risk is said to be a complex construct that several scholars have researched. For instance, Lee et al. (2003) stressed that Jacoby and Kaplan's risk dimensions model (Jacoby & Kaplan, 1972) is inherent and suitable to the MFS study. Featherman & Pavlou

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(2003) investigated the risk model of e-service adoption in the context of internet-delivered services by replacing the physical risk component with the privacy risk factor, which is considered a more significant risk factor in online services based on empirical evidence. As the significant level of perceived risk measurement, Zhao et al. (2008) identified four key risk categories (risk of losing personal control, losing face, and system failure). Equally, Littler & Melanthiou (2006) recognized six main aspects of perceived risk (psychological, security, financial, performance, time, and social) related to the decision of consumer acceptance of internet banking services during the initial stages of market development. Others have also stressed the essential features of risks supporting consumers' decisional intention, like time, financial, performance, social, security, and privacy (Hanafizadeh & Khedmatgozar, 2012).

This study incorporates transaction security risk into the risk dimensions proposed by Featherman & Pavlou (2003), and it advances the study of perceived risk by integrating it. This study addresses perceived risk from four perspectives: privacy, time, security, and money in the form of monetary, based on the findings of previous studies and summarizing the notions of the dimensions of perceived risk.

6.3 Hypothesis Development

6.3.1 Multidimensional Perceived Risk and Overall Perceived Risk

The perception of risk exposure of a mobile money service (MMS) client is a possible barrier to accepting the service. It is then essential to review the various aspects of the risk dimensional to the overall risk and how it might influence the consumers' intention to use MMS.

Regarding the potential perceived risk facet, privacy denotes the ability of an individual or organization to decide on whether, when, and to whom personal or organizational information should be released (Saltzer & Schroeder, 1975). Therefore, privacy differs from security, which is the mechanisms and procedures that control who may use or change the device (i.e., computer, cell phone) or the information stored in it (Saltzer & Schroeder, 1975). Privacy risk involves individual users, their behavior, and relationships with others, while security risks entail risks posed by adversaries attacking or threatening a system (Hong et al., 2004). (Palen & Dourish, 2003) stressed that managing privacy involves handling ever-changing situations rather than implementing existing rules. Services that carefully deal with privacy issues are expected to protect clients from any possible risks, loss, or fraud. Hence, users may have increased trust in the service providers that decrease individual privacy issues and improve overall customer satisfaction (M. Liang et al., 2014).

In terms of the online environment, Liu et al. (2008) found that security and privacy are important factors in predicting Chinese buyers' happiness with online buying. Furthermore, Sakhaei et al. (2014) emphasized the importance of privacy and security in internet banking and their impact on service quality, which affects consumer satisfaction. As a result, customer decision-making is influenced by their perception of risk connected with privacy and security. As a such, security and privacy concerns force customers to devote additional time and effort to protect themselves from fraud and hackers, leading them to regard mobile financial services as a risky way to conduct business (Daneshgadeh & Yıldırım, 2014).

Equally, time risk ascends when clients spend more time dealing with incorrect transactions, putting in the required information, and waiting for site responses, website confirmation, internet server, and download speed (Kaur & Arora, 2020). In the context

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of mobile money, a customer may believe that the service provider will not meet the desired level of service, resulting in monetary loss (perceived financial cost or monetary risk) and time spent learning (perceived time).

In terms of monetary risk, it relates to a consumer's opinion that a particular internet channel (in our case, mobile money services) is more expensive than alternative purchasing channels (Luarn & Lin, 2005). The cost of utilizing MMS to conduct transactions is related to its adoption rate among the unbanked population (Tobbin, 2012). Individuals are more inclined to use mobile money services if they believe the associated cost is reasonable in comparison to other available service options (Luarn & Lin, 2005). Some research in emerging economies, such as China (H. Yao & Zhong, 2011), Brazil (Cruz et al., 2010), and Bangkok (Sripalawat et al., 2011), have identified monetary risk to be a barrier to mobile financial service uptake. Individuals' intentions to evaluate the perceived overall risk would be necessary once they consider the cost of mobile phones high, the cost of obtaining SIM cards high, and the cost of registration and other transaction fees to be high.

The following hypothesis can be made based on the preceding description of the multidimensional risk component with perceived overall risk:

H1. Perceived privacy risk influences overall risk perception in a positive and significant way.

H2. Perceived temporal risk influences perceived overall risk in a positive and significant way.

H3. Security risk perception has a favorable and significant impact on total risk perception.

H4. Perceived monetary risk influences total risk perception in a positive and significant way.

6.3.2 Overall Perceived Risk and Behavioral Intention

Risk perception refers to the likelihood of negative outcomes from the use of online services, such as transaction security, fraudsters' hacking and phishing attempts, internet flaws, or website or app failure (Kesharwani & Singh Bisht, 2012). All of these concerns may deter clients from using MFS. Indeed, factors of perceived risk have been widely considered as critical negative predictors of customers' intents and the adoption of information systems (IS), including mobile money services (MFS) (L. F. Cunningham, Gerlach, & Harper, 2005) (de Kerviler et al., 2016) (Roy et al., 2017). The theory of reasoned action (TAM) can be used to explain the negative relationship between the risk perception and behavioral intention. Attitude, which normally inspires action, can be used to enlighten the negative relationship between perceived risk and behavioral intention (Fishbein & Ajzen, 1975). It is projected that lowering perceived risk will increase customers' desire to transact, based on the consistency of this leading idea. (Kesharwani & Singh Bisht, 2012) clarified this phenomenon in terms of the attitude-action principle, since perceived risk in online transactions reduces behavioral and environmental control perceptions. Customers' behavioral intentions are mitigated as a result of this lack of control. Customers are more inclined to transact online if their risk perceptions of behavioral and environmental anxieties are alleviated, according to the logic of this reasoning. Risk factors are important in mobile services, according to Hanafizadeh et al. (2014), and the higher the risk of utilizing new technology, the lesser the willingness to utilize it. As a result, if a consumer sees increased risks in mobile money services, he or she will be less likely to utilize them. Reduced risk perception with mobile money, on the other hand, will increase customers' willingness to utilize it.

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Given the low penetration rate of MFS and the resulting lack of significant risk-based protection measures, we expect that individuals will develop resistance to this novel technology and generate a negative opinion of it as a new way of payment. As a result, the following theory is put forth:

H5. Perceived overall risk has a negative and significant influence on behavioral intention to use mobile money services.

Figure 6-1 depicts the research model studying customer intention to use mobile money services.

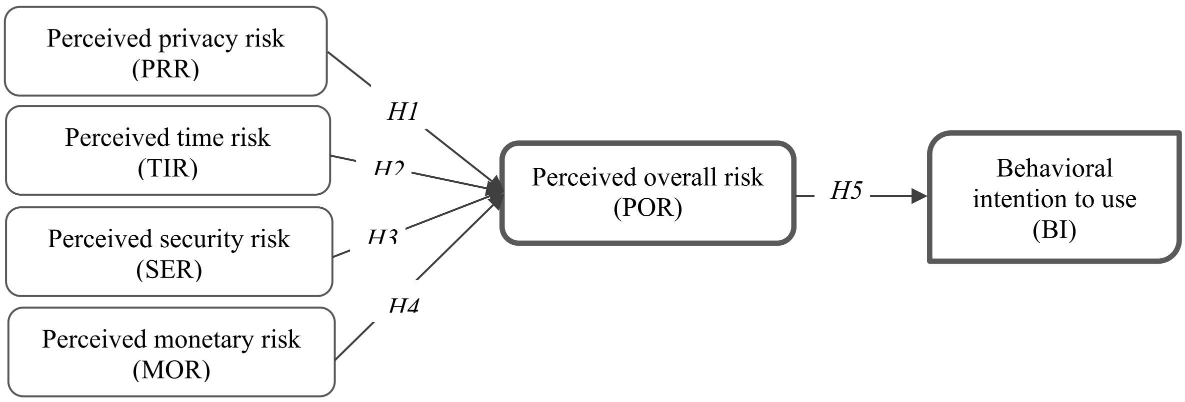

Figure 6-1 Proposed research model

Source: own elaboration

6.4 Research Methodology

A sampling frame involves mobile money clients dwelling in Lome, Togo's capital city, based on the study's aims to explore the multidimensional effect of perceived risk on the total risk perception toward Togolese customers' intention. This study tested the model and hypotheses by collecting quantitative data from a sizable number of participants using survey-based research methods. A structured questionnaire based on the proposed model was prepared and disseminated among Togolese mobile money consumers (potential and present users) (e.g., T-money and Flooz). The investigators filled in the responses provided by respondents concerned about dealing with hard copies of the questionnaire or becoming contaminated and infecting others due to the possibility of virus transmission. The surveys were designed to target customers familiar with financial institutions' various service offerings and knowledgeable enough to respond.

Furthermore, the questionnaire was not lengthy and did not require too much time to fill it. The data collection lasted for one month. A purposive sampling technique was applied to choose the various study areas, and simple random sampling was most used to sample the subscribers. The simple random method was used to give an equal chance to the users of the service. Those applicable to mobile financial services were separately extracted and partially used among the question items presented in the existing literature. Notably, the tools that measure perceived risk privacy were adapted from Cheung & Lee (2001) and Flavián & Guinalíu (2006); perceived time was measured by adjusting the instrument from Nam & Quan (2019) and Yang et al. (2015). The scales of perceived security risk were derived from Featherman & Pavlou (2003), and Yang et al. (2015); the perception of monetary risk was adapted from Kuisma et al. (2007) and Fain & Roberts (1997). The items of perceived overall risk were adapted from Featherman & Pavlou

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(2003), and Roy et al. (2017); constructs regarding the customer's intention to use mobile money services were adapted from Fred D. Davis MIS (1989) and Davis et al. (1989). For clarity, a 5-point Likert scale was employed to measure the level of agreement for every item, starting from strongly disagree (1) to strongly agree (5). According to Field (2006), such scales are essential to reduce biases in a survey. The complete list of items is given in Appendix C. The survey instrument was validated using back-to-back translations from English to French and then French to English. Two experts, including one professional translator, validated the final version. A total of 320 questionnaires were disseminated. We only received 275 completed and usable responses; thus, our response rate was 85.94%. Those omitted were due to errors such as partial response or missing data.

6.5 Data Analysis

6.5.1 Profile of Respondents

The demographic characteristics of the 275 participants are presented in **Table 6-1**, indicating that 53.9% of the respondents were female and 46.1% were male. Most participants were relatively young, with 28% below the age of 25, 34.9% aged between 25 and 34 years, 19.6% between 35 and 44 years, and 17.5% aged 45 years and above. Regarding educational qualifications, 40% of the respondents were secondary school graduates, followed by university degree holders at 26.2%, while 23.3% held a high school (A level) diploma. Only 10.5% of the respondents reported having no formal education.

Table 6-1 Demographic profile of respondents

Variables	Classification	Total (N=275)	
		N	%
Gender	Female	148	53.9
	Male	127	46.1
Age	18-24	77	28
	25-34	96	34.9
	35-44	54	19.6
	45 or more	48	17.5
Education level	No formal education	29	10.5
	Secondary school	110	40
	Higher school	64	23.3
	University	72	26.2

Source: own research result

6.5.2 Structural Equation Modeling

Statistical Package for Social Sciences (SPSS 21) and Analysis of Moment Structures (AMOS 20) were utilized for data analysis to estimate the model parameters. A two-phase approach recommended by Anderson & Gerbing (1988) for structural equation modeling (SEM) was utilized to evaluate the proposed model. The first phase involved assessing the measurement model to investigate the reliability and validity of the relationships between latent and related observable variables. The second phase focused on testing the structural relationship among the theoretical constructs, as outlined by J. F. F. Hair et al. (2006). Additionally, an artificial neural technique was employed to predict and classify the antecedents of perceived overall risk associated with mobile money services.

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6.5.2.1Measurement model assessment

Using AMOS 21 software, confirmatory factor analysis (CFA) was performed to examine the factor structure and validate the scales (Joseph F Hair, Black, Babin, & Anderson, 2010). The suggested model was tested at the early stage for model fit, reliability, convergent validity, and discriminant validity. The model was found to be sufficiently fit with Chi-Square$(x^2) = 1068.904$, Chisq/df $(x^2/df) = 2.104$, goodness of fit index$(GFI) = 0.839$, adjusted goodness of fit index$(AGFI) = 0.823$, normed fit index $(NFI) = 0.900$, Tucker-Lewis index $(TLI) = 0.935$, comparative fit index $(CFI) = 0.944$ and root mean square error of approximation$(RMSEA) = 0.045$.

Second, Cronbach's alpha (CA) and composite reliability (CR) were used to assess the constructs' reliability (Bagozzi et al., 1988). **Table 6-2** shows that CA and CR for each construct were higher than the recommended threshold of 0.7, indicating good internal consistency (Bagozzi et al., 1988) (Bernstein & Nunnally, 1994). The convergent validity of items was evaluated based on the average variance retrieved (AVE). The AVE defines how much variance a construct captures in relation to measurement error. It should be more than 0.5 so that the latent concept may explain more than half of the variance in its indicators (Joseph F Hair, Black, Babin, & Anderson, 2010). The AVE for each construct ranged from 0.571 to 0.664, substantially over the minimum needed threshold of 0.5, as shown in **Table 6-2**. As a result, convergent validity was found for all constructs in this study.

Finally, discriminant validity was evaluated using a correlation matrix or cross-loading criterion (Fornell & Larcker, 1981). The square root of AVEs for each construct should be bigger than the correlations between the relevant constructs (Fornell & Larcker, 1981). **Table 6-2** shows that all diagonal AVE elements were greater than those in the respective rows, meeting Fornell-discriminant Lacker's validity criterion (Fornell & Larcker, 1981). In sum, the above **figures** confirmed the soundness of the measurement model of this research.

Table 6-2 Reliability and validity in CFA

Construct	CR	AVE	MSV	PRR	TIR	SER	MOR	POR	BI
PRR	0.862	0.609	0.057	**0.780**					
TIR	0.855	0.664	0.227	0.144	**0.815**				
SER	0.843	0.577	0.056	0.011	0.235	**0.760**			
MOR	0.856	0.600	0.133	0.238	-0.022	-0.072	**0.775**		
POR	0.811	0.594	0.065	0.232	0.091	0.035	0.255	**0.771**	
BI	0.799	0.571	0.013	-0.004	-0.035	0.086	0.075	0.115	**0.757**

Notes: Off-diagonal values estimate inter-correlation between the latent constructs; diagonal values are squared roots of AVE. Notes: PRR-perceived privacy risk; TIR-perceived time risk; SER-perceived security risk; MOR-perceived monetary risk; POR-perceived overall risk; and BI-behavioral intention to use.

Source: author's computation

6.5.2.2 Structural model assessment

The structural model and associated hypothesized theoretical relationships were the next phase. The structural model's fit statistics ($x^2 = 30.445,\ x^2/df = 1.903,\ GFI = 0.991,\ AGFI = 0.817,\ NFI = 0.941,\ TLI = 0.869,\ CFI = 0.919,\ RMSEA = 0.041$) were above the stated threshold limit, indicating that the model fit was satisfactory. **Table 6-3** summarizes the model's causal path attributes, including standardized path estimates and t-statistics (CR derived from AMOS). The result revealed that the behavioral intention is negatively explained by perceived overall risk ($b = -0.205, p < 0.01$). Perceived overall risk, which is hypothesized to be significantly influenced by

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perceived privacy risk ($b = 0.309, p < 0.001$), perceived security risk ($b = 0.143, p < 0.001$), and perceived monetary risk (b = 0.148, p < 0.001), was supported. However, the path coefficient of perceived time risk ($b = 0.032, p > 0.05$) on the overall perceived risk was recognized as non-significant. The threshold level of t-values is 1.68 at 0.10, 1.96 at 0.05, 2.57 at 0.01, and 3.3 at 0.001. Hence, except for H2 (TIR→POR), all research hypotheses (H1, H3, H3, and H4) were supported (**Table 6-3**).

Furthermore, statistical results from the collinearity test showed no concern regarding multi-collinearity since all variance inflation factors (VIF) and tolerance values were within acceptable limits of 5 and 0.2, respectively (J.F. Hair et al., 2017). Multidimensional risk perception predicts 35 percent of variance for perceived overall risk, with the latter indicating 20.6 percent of intention factors based on R^2 values. These numbers meet the reasonable condition of more than 0.19 to demonstrate the model's validity (Joe F. Hair et al., 2012).

Table 6-3 Results of standardized estimates of the structural model

Hypothesis	Causal path			Path Coefficients	t-value	P-value	Significance?
H1	PRR	→	POR	0.309	8.987	***	YES
H2	TIR	→	POR	0.032	0.951	0.346	NO
H3	SER	→	POR	0.143	4.806	***	YES
H4	MOR	→	POR	0.148	4.477	***	YES
H5	POR	→	BI	-0.205	-3.416	0.003	YES

* p<0.05; ** p<0.01; *** p<0.001 level of significant

Notes: PRR-perceived privacy risk; TIR-perceived time risk; SER-perceived security risk; MOR-perceived monetary risk; POR-perceived overall risk; and BI-behavioral intention to use.

Source: author's Computation

6.5.3 Neural Network Analysis (ANN)

This research adopts a multi-analytical technique by integrating SEM and ANN, one of the most important artificial intelligence methods. Haykin (1999) describes ANN as a massively parallel distributed processor comprising mere processing units with a neural tendency to store and apply experimental information. The acquired knowledge from learning processes is stored in synaptic weights (Francisco Liébana-Cabanillas, Marinkovic, et al., 2018). The neural network model in this study was developed using the statistical package IBM SPSS 21.0, which played an essential part in modern artificial intelligence techniques and was trained by a multilayer perception training algorithm.

Various researchers have considered the most commonly adopted neural network model –feed-forward back-propagation multilayer perceptron (FFBP-MLP) (L.-W. Wong et al., 2021) (Dumor & Gbongli, 2021)in the field of business to assess and predict dependent variables based on independent variables (Sujeet Kumar Sharma, 2019) (Francisco Liébana-Cabanillas, Marinkovic, et al., 2018) (Gbongli et al., 2019). The multilayer perceptron network is a function of predictors (i.e., inputs or independent variables) that reduce the prediction error of target variables (i.e., outputs). Therefore, to train and test the research model in this study, we have applied a multilayer perceptron (MLP) with feedforward-back propagation (FFBP) algorithm. The MLP entails three layers, i.e., input, hidden, and output. The input signals are fed forward, while the error signals propagate backward.

Determining the number of neurons in the hidden layers is crucial in deciding the overall neural network architecture. The analysis examined the network with one to ten hidden nodes. There is no heuristic method to identify the number of hidden nodes in an ANN, so trial-and-error and rules-of-thumb are usually used (F. T. S. Chan & Chong,

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2012) (A. Y. L. Chong, 2013). One of the most commonly known empirically-driven rules-of-thumb concerns the ideal number of hidden neurons, mainly between the number of input and number of output neurons (Blum, 1992). Another rule equals 2/3 of the input and output layers (S. Xu & Chen, 2008). Various scholars recommended other practices that regard the ideal number of hidden neurons based on input and output neurons (Sheela & Deepa, 2013). For instance, Shibata & Ikeda (2009) proposed that the number of hidden neurons (N_h) could be computed as follows:

$$N_h = \sqrt{N_i * N_0} \tag{1}$$

Where N_i – is the number of input neurons and N_0– is the number of output neurons.

Alternatively, the required number of hidden neurons (N_h) estimated in the hidden layer using multilayer perceptron (MLP) were found by Trenn (2008) and computed as follows:

$$N_h = \frac{N_i + N_0 - 1}{2} \tag{2}$$

The crucial points are simplicity, scalability, and adaptivity. Some scholars, including Yao et al. (1999), have also suggested logarithmic dependence, even more straightforward and practical guidelines, between the number of hidden neurons and the number of inputs:

$$N_h = \ln{(N_i)} \tag{3}$$

In the same vein, Fang & Ma (2009) quite similarly stated:

$$N_h = log_2\,(N_i) \tag{4}$$

There is no definitive rule for determining the optimal number of hidden neurons. The number of hidden neurons should be carefully balanced to avoid instability in the model. If the number is too large, the output becomes unstable; if it is too small, the output is also unstable. It is important to note that these guidelines should be tested before the final application. Because there is no dominating rule, simulation software's recommendation is used in various situations (Liébana-Cabanillas et al., 2018). In most circumstances, the network with the fewest hidden neurons that perform best on the testing set should be chosen. The number of hidden neurons selected may be influenced by several other factors, such as the neural network design, sample size, complexity of the activation function, training algorithm, number of hidden layers, and others, which should also be considered. Because there is no dominating rule, simulation software's recommendation is used in a variety of situations (Francisco Liébana-Cabanillas, Marinkovic et al., 2018)

In this study, the number of neurons in a hidden layer was varied to observe the impact of the hidden layers on the neural network's performance. The results revealed that three neurons in the hidden layer were optimal, so they were chosen to train the networks. The network structure settled for data involved an input layer, one hidden layer, and an output layer. The input layer consisted of four neurons, three in a hidden layer and one in the output layer (see Fig. 6-2). The input layer entails four independent variables: the output obtained from Covariance-based structural equation modeling (CB-SEM) (i.e., perceived privacy risk, perceived time risk, perceived security risk, and perceived monetary risk). The output layer was made of one output variable (i.e., perceived overall risk). The nodes' number in one hidden layer was set to 2 based on the above recommendations, and the activation function was set to the sigmoid function in both hidden and output layers (L.-Y. Leong et al., 2013) (Gbongli et al., 2019). Given the improvement of the training effectiveness or shorter training times and better performance, both inputs and outputs were normalized to the range [0,1] (Negnevitsky, 2011).

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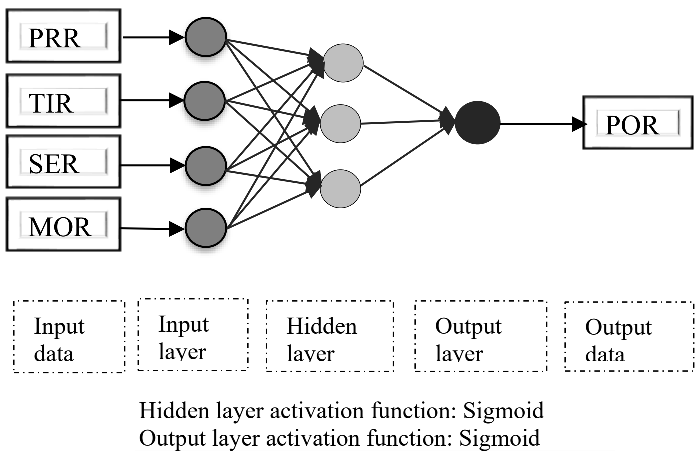

Figure 6-2 Schematic model of ANN MLP 4-3-1
Source: own elaboration

The accuracy can be measured through the root-mean-square of error (RMSE), suggested by Hyndman & Koehler (Hyndman & Koehler, 2006). RMSE is always positive, and the value of 0—revealing a perfect fit—has virtually never occurred in practice. Therefore, for assessing the model's predictive accuracy, the RMSE of training and testing data sets is calculated for all ten neural networks, with the computation of the averages and standard deviations (see **Table 6-4**). Put differently, lower values of RMSE are desired, and the RMSE can be computed below:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_{Obs,i} - X_{true,i})^2} \tag{5}$$

Where $X_{Obs,i}$ be the observed value, $X_{true,i}$ be the actual value considered equally to the model value, and n be the number of data sets, i.e., 275 for this study.

Table 6-4 Neural network validation results

ANN	Input neuron: PRR, TIR, SER, and MOR; output neuron: POR	
	Training	Testing
ANN1	0.1147	0.0415
ANN2	0.1146	0.0398
ANN3	0.1144	0.0411
ANN4	0.1174	0.0317
ANN5	0.1182	0.0339
ANN6	0.1127	0.0449
ANN7	0.1150	0.0409
ANN8	0.1167	0.0342
ANN9	0.1122	0.0457
ANN10	0.1177	0.0310
Mean RMSE	0.1154	0.0385
Standard deviation	0.0073	0.0481

Source: author's computation

As revealed earlier, ten-fold cross-validation was applied to avoid over-fitting, where 90% of the data were considered to train the ANN, whereas the remaining 10% of data points were selected to measure the trained network's prediction accuracy. The RMSE values obtained from the neural network model for training and testing data points are

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minimal (i.e., 0.1154 for training data and 0.0385 for testing data). Therefore, the results obtained are pretty accurate (Francisco Liébana-Cabanillas, Marinkovic, et al., 2018).

Sensitivity analysis: The importance of every independent variable computed as a sensitivity analysis measures how much the value predicted by the network model diverges with different independent variable values (A. Y.-L. Chong, 2013). The relative importance of variables determines the normalized importance, which can be expressed as the ratio of relative importance to its highest relative importance and is also generally disclosed in percentage (Sujeet Kumar Sharma et al., 2019). **Table 6-5** summarizes the average and normalized relative importance obtained from the neural network model.

Table 6-5 Importance of constructs

Network	Output neuron: perceived overall risk (POR)			
	PRR	TIR	SER	MOR
ANN1	0.732	0.121	0.055	0.091
ANN2	0.678	0.141	0.018	0.163
ANN3	0.737	0.141	0.034	0.089
ANN4	0.652	0.178	0.029	0.142
ANN5	0.511	0.081	0.168	0.24
ANN6	0.696	0.164	0.025	0.116
ANN7	0.79	0.119	0.041	0.05
ANN8	0.753	0.119	0.031	0.097
ANN9	0.754	0.132	0.045	0.068
ANN10	0.573	0.184	0.072	0.171
Average relative importance	6.876	1.38	0.518	1.227
Normalized importance (%)	100.0	20.1	7.5	17.8

Source: author's computation

According to the sensitivity analysis performance, perceived privacy risk was the most significant predictor of the overall perceived risk, followed by perceived time risk, perceived monetary risk (financial risk), and perceived security risk. Interestingly, perceived time risk contradicts the results obtained from SEM. It was found not supported in the SEM results. However, it is the second most influential element in the neural network model, predicting perceived overall risk toward mobile payment services. The disparity between results achieved by the structural equation model and the neural network model can be clarified by the nonlinear and non-compensatory nature of the neural network model and the much higher-order prediction capability of the later model.

6.6 Conclusion and Implication

The rate of mobile phone adoption for money transfers does not yet match the increasing prevalence of smartphone use for mobile financial experiences. The low level of mobile money service situations suggests the importance of considering the perceived risk that might impede consumers from conducting e-money transactions through smartphones. Moreover, the COVID-19 pandemic required people to use digital payment applications. However, not all people are comfortable and even willing to use e-money. Though, they are forced to some extent due to the outbreak of the COVID-19 virus. As such, many unpredicted hazards in the environment of modern society can only be limited but not removed entirely, and rational consumers are concerned regarding both benefits and uncertainties in the decision-making process (Mitchell, 1999). Therefore, consumers could be impacted by risks that they perceive (S. Chan & Lu, 2004).

By examining data collected from mobile phone money users (current and potential), this research tested and established perceived risk as a multidimensional factor that

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entailed various risk facets. In providing more detail, the values of reliability indices, validity indices, and all other fit indices were within the established thresholds (Joseph F Hair, Black, Babin, Anderson, et al., 2010). Apart from SEM results, this study employed a neural network technique to rank the determinants of overall perceived risk while offering evidence to validate SEM results.

This study used four dimensions of perceived risk (i.e., privacy, time, security, and monetary risks) as potential antecedents of perceived overall risk. Interestingly, only perceived time risk has no statistically significant impact on perceived overall risk. Generally, the SEM results, except for time risk, are similar to the earlier studies on conceptualized facet-based perceived risk (Featherman & Pavlou, 2003) (Ritu Agarwal & Prasa, 1998). Each dimension of perceived risk positively influences the overall perceived risk of mobile money services. Moreover, the moderate to weak positive relationships between the perceived overall risk and their antecedent provide further reinforcement that risk can be researched as a multidimensional phenomenon (G. W. Zikmund & Scott, 1974). These findings imply that mobile money's privacy, security, and monetary risk play an essential role in adopting mobile-based services by Lome -Togo residents.

Importantly, SEM results revealed that privacy risk strongly and significantly influenced the overall risk construct (H1: beta = 0.309, p-value < 0.001), making it the most relevant perceived risk facet of consumers' decision-making when evaluating mobile money services. Conversely, consumers are less concerned about security risks (H3: beta = 0.143, p-value < 0.001). Logically, it might seem that privacy is superfluous when security is present, and security is redundant when privacy is present (D. J. Kim et al., 2008). The ranking obtained from ANN analysis also supports the influence of privacy risk regarding the overall risk to be the most influential risk factor. This implies that consumers' concerns about privacy contribute greatly to risk perception with money transfers using mobile devices. This result corroborates the earlier works (Turel et al., 2007). Although mobile money incorporates various advantages, perceived risks are associated with this service, particularly potential fraud. The most recurrent forms of fraud allied with mobile money entail identity theft, fake currency deposits, scams such as promotional scams, and phishing, intensified by the abundant use of SIM cards. Acceptance regulations can avoid these illegal activities to reduce and manage risks while still progressing regarding the business goals. A collaborative approach between promoters of mobile financial services, mobile network operators, and regulators should tighten the existing digital consumer protection laws. An efficient mechanism for recourse, compensation, and remedy should be set up to benefit the victims of fraud and cybercrime on the mobile money platform. Therefore, when consumers perceive the effectiveness of the privacy policy, privacy concerns will reduce (S. Sharma et al., 2021).

This study also confirms the positive impact of the monetary risk (i.e., perceived financial risk) on consumers' perceived overall risk in general. The lower the cost, and trivial remains the perception of risk. From this view, the involvement aspect of the risk is well pronounced when the price or cost is high, which might prompt consumers to think about the risk of losing money (Choffee & McLeod, 1973). While privacy risk significantly and strongly influenced the overall risk, monetary risk (financial risk) did not reveal such an effect. Perceived monetary risk (H4: beta = 0.148, p-value < 0.001) has been considered moderately by consumers in the perception of overall risk toward the adoption of mobile money, although these dimensions are primarily of concern in studies on consumer adoption of electronic financial services (Luarn & Lin, 2005) (Smith, 2006).

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Potential enlightenment could be found in consumer behavior studies that revealed that perceived financial risk is very substantial in some cases. It plays a role separate from the other risk facets (Stone & Grønhaug, 1993). Another justification could also be that the possibility of spending additional money for a mobile service was not such a big concern for people already accustomed to cell phone use.

By comparing the SEM results and the ANN analyses, the main difference lies in the strength of one variable, which is perceived time risk. The ANN analysis increases the relative importance of the risk perception of time towards the overall risk, whereas; time risk is not statistically significant in SEM. This finding could imply that the perception of risk regarding the time might not have a linear statistical significance and direct influence on the aggregate risk. Concerning the non-validation of perceived time risk, it can be suggested that because mobile money services are a relatively new technology in respondents' view, they lack experience. They might not focus much on the time spent using the designated service. Therefore, when the technology is deemed as challenging to learn and/or time-consuming to prepare and use or is in some other way perceived as threatening, it possibly will not be used (Carr Jr., 1999). It may also be that consumers do not recognize a perception of time as an assurance of risk perceived. This suggests that the impact of time risk perceived is worthy of further development in future studies. MFS companies are encouraged to continue easing the transaction process of MFS in terms of time spent.

Perceived overall risk has a significant negative influence on adoption usage intention. This finding is consistent with earlier findings where the perceived risk is a key factor leading to customer resistance in the usage of mobile and online technologies in Malaysia, Kuwait, Brazil, India, Germany, and Singapore (Al-Jabri & Sohail, 2012) (Amin, 2008) (Cruz et al., 2010) (Thakur & Srivastava, 2014) (Koenig - Lewis et al., 2010) (Riquelme & Rios, 2010). Mobile money services payments involve significant uncertainty and risk, and service providers may consider applying advanced encryption technologies such as a secured socket layer and third-party certification to build trust in mobile payments (M. Li et al., 2012).

Therefore, this research, which contributes to the perceived risk theory using perceived risk as a multi-dimensional framework within the scope of modern mobile financial service research, is appropriate. The study determines that perceived risk, particularly privacy concerns, prevailed irrespective of the forceful adoption of mobile money due to the COVID-19 pandemic. The use of the two-stage predictive-analytic (Scott & Walczak, 2009) (Gbongli et al., 2020) (Gbongli, 2017), such as SEM–neural network analysis, offers a more holistic understanding of inhibitors determinant of mobile money acceptance specifically and IT adoption generally and therefore provide substantial methodological support from the statistical point of view. This is because the non-compensatory neural network analysis can complement the weaknesses of compensatory and linear SEM analysis. The study has offered a novel perspective in assessing the key factors of mobile money service acceptance, enriching and closing up the knowledge gaps in the current body of knowledge.

This research provides valuable insights into how telecommunication service providers, mobile financial software developers, and mobile money service (MMS) providers improve and keep their consumer base. As a result of the findings, service providers should concentrate their efforts on decreasing risk factors and assisting and inspiring potential customers. MMS companies should promote the fact that mobile money transfer is a safe service by providing good customer feedback at the point of sale

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or through the media. Money-back guarantees could be added to the list of successful risk-prevention strategies, so customers feel more at ease and secure with the system. To summarize, mobile money is a growing trend in Togo, with much room for growth. It is time for the country to adopt the service following the COVID-19 outbreak.

6.7 Limitations and Future Research

Certain limitations of this study could lead to more research in the future. Customers from a single country were used to test the relationships between the components. As a result, conducting similar investigations in diverse situations will be informative in strengthening the nuances of such constructs in the mobile financial service technology adoption literature. The moderating influence of any variable is not included in this study's research model. As a future study, it is suggested that the moderating effect of demographic characteristics be investigated to understand better the barriers to mobile money adoption from a different population segment. Researchers could investigate adding other components like effort expectancy and trust to the model in the future to improve its robustness and produce a better prediction of customers' intention to use mobile money. Finally, given the stigma and risk of using banknotes, analyzing the preference for mobile money in high-risk contexts (such as food courts and hospitals) would be timely while limiting the spread of COVID-19 and other microorganisms.

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Chapter 7 Concluding Scholarly Implications of Integrated Findings

Over the past two decades, the range of digital financial services accessible through mobile phones has grown significantly. Whereas innovations play a critical role in making our life easier, their adoption by users is influenced by several factors. Notably, the recent rise of mobile phones in Africa has led to a heightened interest in mobile financial services (MFS), including mobile banking, mobile payment, and mobile money, which can be identified as the three domains of the MFS field (Shaikh et al., 2022). With the increasing use and demand for smartphones, research remains ongoing to assess customer, policy, management, and theoretical viewpoints in the MFS field (Chawla & Joshi, 2017). Most Previous efforts to synthesize knowledge in the MFS field have been sparse in scope and purpose.

This thesis aims to offer a systematic review of the literature on the MFS adoption and, to some extent, the adoption of mobile money services through the technology acceptance model (TAM). By leveraging AI strategies, including structural equation modeling (SEM) and artificial neural networks (ANN), this work provides a comprehensive understanding of the drivers of MFS adoption. These multi-analytical methodologies enable robust decision-making and prediction, crucial for enhancing financial inclusion in developing countries. We separately examined MFS and mobile money services using quantitative survey data to reveal adoption drivers through these advanced analytical techniques. The primary contributions of this work include integrating AI strategies to predict factors influencing consumer acceptance of MFS and categorizing different types of MFS based on user preference. The findings are presented and compared with existing literature, highlighting significant contributions to academic and practical fields while acknowledging limitations. This research offers valuable insights for financial institutions, service providers, policymakers, and scholars, ultimately promoting financial inclusion through the effective adoption of mobile financial services.

7.1 Unveiling the Full Picture: Comprehensive Analysis Results of MFS Acceptance

The results of the five publications provide the answer to the research problem (**Figure 1-3** of Chap 1, i.e., an overview of the dissertation structure from the research problems, goals, and publications) so that the outlined objectives previously mentioned can be achieved.

Commencing the *second chapter*, we addressed the research problem (**Figure 1-3** of Chap 1) of performing a comprehensive synthesis and analysis of the motivating factors that prompted consumers to utilize mobile financial services (MFS) during the last decade, despite it being the latest study developed and published in this field. The results indicate that the unified theory of acceptance and usage of technology (UTAUT) followed by the technology of acceptance model (TAM) are the core conceptual frameworks and models adopted to understand consumers' MFS adoption. Six key factors emerged as the strongest predictors of behavioral intention to use MFS: (i) attitude, (ii) perceived ease of use, (iii) performance expectancy, (iv) habit, (v) social norms, and (vi) perceived usefulness. A Technological-Personal-Environmental (TPE) framework was developed to guide future research in this area. Notably, attitude toward adoption emerges as a critical determinant in technology acceptance, offering valuable insights for managers. Therefore, products with ease of use, low-performance expectancy, and usefulness are unlikely to influence consumer attitudes and intentions to adopt. Firms should keep this in mind, especially during the product design stage. It is believed that the results of this systematic review will provide an inclusive source for conducting further research in MFS. It should be noted that the results depend significantly on the criteria for searching and selecting the literature (cf. (Gbongli, 2022a) or Chapter 2 of the Thesis).

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Chapter three of the thesis focuses on the research problem outlined in **Figure 1-3** of Chapter 1, which pertains to the lack of a comprehensive overview of the TAM model and its extensions in MFS. The study aims to bridge this gap by conducting a literature review in the relevant field and including all relevant studies. These studies' primary variables identified as predictors of behavioral intention are (i) perceived security, (ii) compatibility, (iii) subjective norm, (iv) trust, (v) facilitating condition, (vi) self-efficacy, (vii) perceived mobility, and (viii) risk. This research emphasizes the importance of consumers' perceptions of MFS regarding service quality and how technology acceptance theories can enhance our understanding of user intentions. However, it is essential to note that the findings are significantly influenced by the criteria used to search and select the literature(cf. Gbongli (2022) or Chapter 3 of the Thesis).

Chapter four focuses on the research objective of investigating the impact of customers' trust and perceived risk on the acceptance of MFS and the prioritization of MFS types (**Figure 1-3** of Chapter 1). To accomplish this, we conducted a multidimensional analysis of the trust and risk model's effects on MFS and then used the results to classify MFS types according to the preferences of experts and experienced MFS users in Togo. Our research found that trust in the vendor, the technology, and inherent trust (i.e., dispositional trust) played a crucial role in shaping overall trust levels. It revealed that the perceived risk associated with privacy was a critical factor influencing perceived risk. We also discovered that dispositional trust and general trust played crucial roles in driving MFS usage behavior. Using the TOPSIS approach, we classified mobile money transfer as the most popular MFS application, followed by mobile payment and mobile banking. These results are consistent with the findings of other studies using the Analytic Hierarchy Process (AHP) on similar topics. The study offers a novel and practical modeling and classification concept for researchers, company managers, and experts in Information Technology (cf. (Gbongli et al., 2020) or Chapter 4 of the Thesis).

Chapter five focuses on the research problem of the drivers of sustainable adoption of mobile money services in Togo, which are not well understood, and the lack of a comprehensive analytical approach to address this problem (as shown in **Figure 1-3** of Chapter 1). To achieve this, the fifth Chapter of the study used the structural equation modeling–artificial neural networks (SEM–ANN) approach to evaluate the adoption of mobile money in Togo. The TAM was extended by incorporating self-efficacy, technology anxiety, and personal innovativeness. The study results showed that self-efficacy was the most important factor and strongly correlated with mobile money's perceived ease of use and usefulness. The study revealed that mobile money users in Togo value both ease of use and usefulness, and those who believed in their ability to use mobile money were more likely to find it useful. It also found that personal innovativeness had a significant relationship with the intention to use mobile money, and individuals with higher levels of personal innovativeness were more likely to develop positive feelings toward using technology. Finally, the study highlights the crucial role of attitude in shaping behavioral intention (cf. Gbongli et al. (2019) or Chapter 5 of the Thesis).

Chapter six of our study centers on the research objective outlined in **Figure 1-3** of Chapter 1, which examines how customers' perceived risk affects their acceptance of mobile money during the COVID-19 pandemic using a multi-analytic methodology. Our findings largely support the hypotheses derived from the literature, and we discovered that perceived privacy risk (PRR) emerged as the most significant predictor of perceived overall risk (POR), which, in turn, negatively impacts behavioral intention (BI) to use mobile money services (MMS). These results emphasize the need for careful consideration of privacy risks when adopting mobile services in Togo. It is important to note that our results are based on survey data and rely on a simple model, but they provide valuable insights for both theory and practice on the factors influencing mobile money adoption. Service providers can promote citizens' trust by offering clear instructions on using MMS safely and addressing any privacy breaches or security issues that may arise. Ultimately, our study fills the literature gap on MMS acceptance and provides

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practical guidance for evidence-based decision-making using the SEM-ANN methodology (refer to Gbongli (2022b) or Chapter 6 of the Thesis).

7.2 Summary of Findings

This dissertation predicts factors influencing consumer acceptance of mobile financial services (MFS) and categorizes MFS types based on user preference using multi-analytical methodologies. It includes five studies: three on MFS and two on mobile money services.

Table 7-1 below provides an overview of the key predictors of mobile financial services (MFS), the most frequently used drivers based on the Technology Acceptance Model (TAM), and both significant and non-significant relationships reported in the remaining chapters. Chapters 5 and 6 utilized a Structural Equation Modeling (SEM) and Artificial Neural Network (ANN) methodology to examine MFS, resulting in two columns for each chapter that offer information on the critical factors and their respective importance levels.

Table 7-1 List of significant and non-significant relationships

Independent/ Input neuron	Dependent/ Output neuron	Chapter						
		$2\ MFS$	$3\ MFS$	$4\ MFS$	$5\ MM_{(SEM)}$	$5\ MM_{(ANN)}$	$6\ MM_{(SEM)}$	$6\ MM_{(ANN)}$
Performance Expectancy(PE)/ Perceived Usefulness(PU)	Behavioral Intention	*						
Attitude (AT)		*			*	$1_{(PI)}$		
Effort Expectancy (EE)/ Perceived Ease-of–Use (PEOU)		*						
Habit (HB)		*						
Subjective Norms (SN)		*	*					
Perceived security (PS)		*	*					
Facilitating Condition (FC)/Compatibility			*					
Trust (TR)/(General Trust)			*	*				
Self-Efficacy (SE)			*					
Perceived Mobility (PM)			*					
Perceived Risk (PR)/Aggregate or Overall perceived risk)			*	*			*	
Personal innovativeness (PI)					*	$2_{(PR)}$		
Dispositional Trust (DT)	General Trust			*				
Technology Trust (TT)				*				
Vendor Trust (VT)				*				
Perceived Privacy Risk (PRR)	Aggregate perceived risk			*			*	$1_{(TIR,MOR.SER)}$
Perceived security Risk (SER)				*			*	$4_{(PRR,TIR,MOR)}$
Perceived Time Risk (TIR)				n.s.			n.s.	$2_{(PRR,MOR,SER)}$
Perceived cost (PC)/ Perceived monetary risk (MOR)				*			*	$3_{(PRR,TIR,SER)}$
self-efficacy (SE)	PEOU				*	$1_{(TA)}$		
Technology anxiety (TA)	PEOU				*	$2_{(SE)}$		
self-efficacy (SE)	PU				*	$2_{(PEOU)}$		
Technology anxiety (TA)	PU				n.s.			
PEOU	PU				*	$1_{(SE)}$		
PEOU	AT				*	$1_{(PU,PI)}$		
PU	AT				*	$2_{(PEOU,PI)}$		
PI	AT				*	$3_{(PEOU,PU)}$		

Notes: MFS: Mobile financial services; MM_{SEM}: Mobile money study with Structural Equation modeling; MM_{ANN}: Mobile money study with Artificial Neural Network; n.s.= No statistically significant effect

Source: own research result

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The study combined some constructs such as (i) perceived usefulness (TAM), (ii) relative advantage (DOI), (iii) performance expectancy (UTAUT), extrinsic motivation, job fit, and outcome expectations into one construct: performance expectancy, as they were deemed equivalent by Venkatesh et al. (2003c). In the same vein, (i) compatibility (DOI) and (ii) facilitating conditions (UTAUT2) were both classified as facilitating conditions. Effort expectancy was used to capture the concepts of (i) perceived ease of use and (ii) complexity in the UTAUT. In chapter 4, the adoption of MFS is reflected as behavioral intention, general trust as trust, and aggregate perceived risk as risk.

In **Table 7-1**, the significant hypothesis in the second row of the 5MM $_{(SEM)}$ column suggests that attitude significantly influences predicting mobile money behavioral intention when using the SEM methodology in chapter 5. Regarding intention, (i) perceived risk was significant in three studies, while (ii) attitude was significant in two studies, with greater relative importance than personal innovativeness. Additionally, (iii) subjective norms, perceived security, and trust were significant in two studies. For perceived risk, (iv) perceived privacy risk was significant in two studies, with higher importance than time, monetary, and security risks.

For non-significant hypotheses, the Table highlights the statistically non-significant impact of perceived time risk on the aggregate perceived risk for MFS adoption (chapter 4) and mobile money service adoption (chapter 6). Moreover, the impact of technology anxiety on mobile money's perceived usefulness (chapter 5) was also non-significant.

7.3 Consistency and Compatibility of Findings Across Timing, Samples, Methodology

In order to confirm the efficacy of the approach taken in this dissertation and to distinguish it from other works, a comparison of the results obtained using various methods will be carried out. This will examine how different factors, such as timing, samples, and scientific methodologies, have influenced the outcomes. Through this analysis, the dissertation aims to highlight the unique contributions of its approach and offer insights into the factors that can impact research outcomes.

The comparison will be aided by **Table 7-1** (List of significant and non-significant relationships), **Table 7-2** (Summary of Data collected and methodology adopted), and **Table 7-3** (Comparison of MFS type between outputs of TOPSIS and AHP techniques). Such a practice ensures consistency and compatibility in the findings and supports the conclusion.

Consistency and compatibility regarding different timing: In chapters 4 and 6, the study examined the multifaceted perceived risk factors (as listed in **Table 7-1**) at different periods of data collection (March to May 2017 and September to November 2021, respectively, as shown in **Table 7-2**). By comparing two datasets (one in 2017 and the other in 2021 during this COVID-19 global crisis) with the same variables and applying the same SEM methodology, the study found that perceived privacy risk remains the most critical antecedent of perceived overall risk, which negatively affects the behavioral intention to use mobile financial services or mobile money service. The results were generally consistent, with a slight difference in the path coefficients. However, these findings partially align with earlier research on the COVID-19 pandemic's impact on mobile payment adoption, suggesting that perceived risk is moderated by perceived security (Belanche et al., 2022). Although the sample size and the data collection period differ between the study of chapters 4 and 6 (See **Table 7- 2**), this particularity does not affect the comparison results.

Understanding users' behaviors is an efficient way to analyze new technology adoption and develop an appropriate strategy for optimizing users' experiences. We can conclude that perceived risk, particularly privacy concerns, prevailed irrespective of the forceful adoption of mobile money due to the COVID-19 pandemic. This implies that the situations may not change

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over time within the Togolese respondents. Therefore, this present research, which contributes to the perceived risk theory using perceived risk as a multi-dimensional framework within the scope of modern mobile financial service research, is appropriate. More research is required to encourage MFS companies to build trust-based strategies to improve service adoption.

Consistency and compatibility concerning the different samples and applied methodology: **Table 7-3** compares the MFS types obtained from two well-known MCDM techniques, TOPSIS and AHP. The rankings of alternatives obtained by both methods in the same dataset are similar, with mobile money being the most preferred MFS major category, followed by mobile payment and mobile banking. According to the study, the decisions made by different methods should have varied if there were discrepancies in the dataset. Chapters 5 and 6 utilized a hybrid SEM and ANN methodology (as shown in **Tables 7-1** and **7-2**). The findings from both methods are consistent, with trivial differences. Factors that revealed greater significance from the SEM technique also have the highest normalized importance with the ANN methodology. Given the result of Chapter 5, the path coefficient between self-efficacy and perceived usefulness is 0.163 ($p < 0.01$), with the highest normalized importance. The major difference between the two methods lies in the strength of the effect of the two constructs relating to innate personal ability and personality traits. The ANN analysis increases the relative importance of self-efficacy in the ease of using mobile money transfer, and personal innovativeness is improved in terms of its effect on users' attitudes and intentions to use mobile money.

The method of multi-analytical data study, as suggested by Silberzahn et al. (2018), can be employed to assess the level of confidence that can be attributed to the conclusions drawn from the research. Overall, the SEM-ANN methodology used in Chapters 5 and 6 is consistent, with ANNs being better than SEM in learning, predicting, and clarifying various factors influencing mobile money adoption. However, SEM supports causal analysis, which is limited in ANN application. This finding is consistent with earlier research on mobile banking adoption (Sujeet Kumar Sharma, 2019), suggesting that the integrated approach (SEM-ANN) contributes more to sharpening the understanding of the model variables' effect than using a single technique.

Table 7- 2 Summary of Data collected and methodology adopted

Chapters	Data set timing	Sample	Methodology
Chapter 4	March-May, 2017.	538 MFS users with SEM, and 74 both MFS experienced users and experts for TOPSIS and AHP	SEM, AHP, TOPSIS
Chapter 5	Jan- Feb 2019	539 users of mobile-based money	SEM, ANN
Chapter 6	Sept- Nov 2021	275 respondents of mobile money services	SEM, ANN
Recall that Chapter 4 is the follow-up of the previous MFS adoption study with SEM-AHP methodology (Gbongli, 2017) on the same data set but adopting a different methodology with SEM-TOPSIS.			

SEM: Structural equation modeling, AHP: Analytic hierarchy process, TOPSIS: Technique for order of preference by similarity to an ideal solution, ANN: Artificial neural network.

Source: own research result

Table 7- 3 Comparison of MFS type between outputs of TOPSIS and AHP techniques

Mobile financial services alternative	TOPSIS % distribution of coefficient	TOPSIS Rank	AHP % distribution of coefficient	AHP Rank
Mobile money	46.68%	1	60%	1
Mobile payment	38.24%	2	24.49%	2
Mobile banking	15.07%	3	15.26%	3

Source: own research result

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7.4 Main Research Contributions

This study makes significant contributions to research and practice by advancing knowledge and offering direct implications for financial institutions, service providers, IT and marketing departments, users, and scholars. These contributions, based on identified research gaps and objectives, include leveraging AI strategies to provide a comprehensive understanding of the drivers of mobile financial services (MFS) adoption. By integrating structural equation modeling (SEM), artificial neural networks (ANN), and multicriteria decision-making techniques (MCDM), the study offers a robust framework for understanding user behavior and enhancing MFS adoption, thereby contributing to financial inclusion in developing countries.

7.4.1 Key Contributions

- **C1 – Systematic Literature Review:** Conducted the first systematic literature review (SLR) in mobile financial services (MFS) over the last ten years, incorporating a weight analysis and encompassing the COVID-19 pandemic period. This review introduced a framework categorizing common MFS constructs into Technological, Personal, and Environmental dimensions, providing a detailed understanding of the critical drivers, models, and theories of MFS acceptance.
- **C2 – Technology Acceptance Model (TAM) Integration:** Utilized the technology acceptance model (TAM) to investigate the adoption of MFS through a sustained meta-analysis integrating the TAM framework and the PRISMA statement. This analysis contributes to a comprehensive understanding of the primary drivers behind MFS acceptance, advancing knowledge in this domain.
- **C3 – Trust and Risk Factors:** Identified trust and risk as primary factors influencing MFS adoption, introducing a novel benchmark methodology to assess their impact. The study confirmed the causal relationship between trust and risk, providing clarity on these complex concepts and highlighting the importance of trust-building strategies in low-trust societies.
- **C4 – Multi-Analytical SEM-ANN Approach:** Demonstrated the benefits of integrating structural equation modeling (SEM) with artificial neural network (ANN), one of the AI (Artificial Intelligence) analysis techniques to investigate MFS adoption. This multi-analytical approach validates SEM results and identifies linear and complex non-linear relationships, increasing confidence and validity in the research outcomes.
- **C5 – Extended TAM Framework:** Proposed a novel research model combining the TAM framework with additional constructs such as self-efficacy, technology anxiety, and personal innovativeness. This multi-analytical SEM-ANN technique filled gaps in previous studies and provided a deeper understanding of individual attitudes and behavior towards mobile money in a developing country context.
- **C6 – Risk Perception During COVID-19:** Conducted the first systematic exploration of the relationship between risk perception and mobile money services (MMS) adoption in Togo during the COVID-19 pandemic using a multi-analytic methodology. The findings highlighted perceived privacy risk (PPR) as the most significant factor affecting overall perceived risk (POR), which negatively influences the intention to use MMS.
- **C7 – Practical Implications for Financial Inclusion:** The research offers valuable insights for practitioners to develop, enhance, and implement MFS that garner widespread consumer acceptance. Recommendations include prioritizing user-centered design, awareness campaigns, incentives, and ensuring data security and privacy to foster the adoption of mobile digital financial services and promote financial inclusion.

7.4.1 Selected New Scientific Findings

1. **Novel Framework for MFS Constructs:** Introduced a framework categorizing

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common MFS constructs into Technological, Personal, and Environmental dimensions.

2. **Validation of SEM-ANN Methodology:** Validated the SEM-ANN methodology as an effective approach for studying MFS adoption, demonstrating the synergy between traditional SEM and advanced AI techniques like ANN.
3. **Key Predictors of MFS Adoption:** Identified key predictors of MFS adoption, including perceived usefulness, ease of use, and trust, which are crucial for enhancing user acceptance.
4. **Impact of COVID-19 on MFS Acceptance:** Conducted a systematic literature review revealing the impact of the COVID-19 pandemic on MFS adoption and acceptance.
5. **Trust and Risk Benchmark Methodology:** Developed a novel benchmark methodology to assess the impact of trust and risk on MFS adoption, providing a new perspective on these factors.
6. **AI-Driven Insights for Financial Inclusion:** Leveraged AI strategies, particularly the use of ANN, to provide deeper insights into customer behavior and enhance the understanding and prediction of MFS adoption.

7.5 Policy Analysis

The findings of this dissertation underscore the importance of perceived usefulness, perceived ease of use, and trust in the adoption of mobile financial services (MFS). Furthermore, self-efficacy and personal innovativeness significantly influence attitudes towards mobile money, highlighting the interplay between technological and personal factors in driving MFS adoption. This policy analysis section aims to translate these scientific insights into actionable recommendations for policymakers, financial institutions, and other stakeholders to enhance the adoption of MFS and promote financial inclusion.

7.5.1 Enhancing Technological Infrastructure

Recommendation:

- Invest in robust and reliable communication networks to support the widespread use of Internet-enabled phones, smartphones, and tablets, ensuring seamless access to mobile financial services.

Rationale:

- The accessibility and reliability of communication networks are foundational to the success of MFS. Enhanced infrastructure will reduce technical barriers and improve user experience, increasing perceived ease of use and usefulness.

7.5.2 Building Trust and Reducing Perceived Risk

Recommendation:

- Develop and implement comprehensive data privacy and security policies to protect users' information and build trust in mobile financial services.
- Conduct regular audits and transparency reports to demonstrate commitment to data security.

Rationale:

- Trust and perceived risk are critical factors influencing MFS adoption. Effective data privacy and security measures can mitigate perceived privacy risk, enhancing overall trust and encouraging adoption.

7.5.3 Promoting User Education and Digital Literacy

Recommendation:

- Launch educational campaigns to improve digital literacy, focusing on the benefits and

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safe use of mobile financial services.
- Provide resources and training programs to increase users' self-efficacy in navigating digital financial platforms.

Rationale:
- Increased digital literacy and self-efficacy can significantly enhance users' confidence in using MFS, addressing concerns related to technology anxiety and perceived complexity.

7.5.4 Leveraging AI and Multi-Analytical Approaches
Recommendation:
- Utilize AI-driven strategies, such as the SEM-ANN approach, to analyze user behavior and predict adoption patterns, enabling personalized and targeted financial services.
- Incorporate AI in developing user-centric applications that can adapt to individual preferences and usage patterns.

Rationale:
- AI strategies provide deeper insights into customer behavior, allowing for the development of tailored services that meet specific user needs. This personalization can improve user satisfaction and adoption rates.

7.5.5 Encouraging Innovation and Personalization
Recommendation:
- Foster an environment that encourages personal innovativeness by supporting startups and financial technology (FinTech) initiatives that introduce innovative MFS solutions.
- Offer personalized financial products that cater to the diverse needs of different user segments, including underserved and unbanked populations.

Rationale:
- Innovation drives the evolution of MFS, and personalized products can address unique user requirements, enhancing perceived usefulness and overall adoption.

7.5.6 Facilitating Financial Inclusion During Crises
Recommendation:
- Implement emergency response strategies that leverage mobile financial services to provide uninterrupted financial access during crises such as the COVID-19 pandemic.
- Develop contingency plans that utilize digital financial platforms to distribute financial aid and support to affected populations swiftly.

Rationale:
- Crises can disrupt traditional financial services, but MFS can offer resilient and flexible solutions. Ensuring their availability during emergencies can maintain financial stability and inclusion.

7.6 Research Limitations and Suggestions for Future Research

Despite the valuable contribution of this study to the mobile financial services domain, certain limitations exist, justifying further investigations and research. These limitations mainly pertain to factors beyond the researcher's control. It is recommended to address these limitations by replicating the study's theoretical models and methodology across different samples, countries, and cultural groups, using various technologies to validate the findings. Additionally, incorporating new studies as they are published can strengthen the systematic literature review and provide additional insights.

Regarding the weight analysis conducted in the systematic literature review, a notable limitation was the time frame in which the studies were developed, which concluded prior to the completion of the remaining studies included in the review. This limitation restricted the

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ability to test the model with the most commonly used constructs in the literature, highlighting the need for further investigation.

Furthermore, the review was limited to studies from the Scopus database, excluding conference publications, editorials, and book chapters. Expanding the scope to include a broader range of databases and studies may lead to variations in the significance of variables and relationships identified.

Lastly, the study solely examined the adoption of mobile financial services from a consumer perspective. Future research could explore the adoption of mobile money services by different stakeholders, such as comparing the level of intention and acceptance among various financial institution market shares.

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Corresponding Publications of the Author

Papers of the Cumulative Dissertation

The following papers are part of the cumulative dissertation. The order of the list corresponds to the order in which the articles appear in the dissertation.

[1] **K. Gbongli,** "A Systematic Review and Weight Analysis of Mobile Financial Services Adoption Literature from 2011 to 2021," Theory, Methodol. Pract., vol. 18, no. 2, pp. 23–49, 2022, doi: 10.18096/TMP.2022.02.02.

[2] **K. Gbongli**, "Understanding Mobile Financial Services Adoption through a Systematic Review of the Technology Acceptance Model," Open J. Bus. Manag., vol. 10, no. 05, pp. 2389–2404, 2022, doi: 10.4236/ojbm.2022.105119.

[3] **K. Gbongli**, Y. Xu, K. M. Amedjonekou, and L. Kovács, "Evaluation and Classification of Mobile Financial Services Sustainability Using Structural Equation Modeling and Multiple Criteria Decision-Making Methods," Sustainability, vol. 12, no. 4, p. 1288, Feb. 2020, doi: 10.3390/su12041288.

[4] **K. Gbongli**, Y. Xu, and K. M. Amedjonekou, "Extended Technology Acceptance Model to Predict Mobile-Based Money Acceptance and Sustainability: A Multi-Analytical Structural Equation Modeling and Neural Network Approach," Sustainability, vol. 11, no. 13, p. 3639, Jul. 2019, doi: 10.3390/su11133639.

[5] **K. Gbongli**, "Assessing perceived risk in mobile money adoption under COVID-19: a combined sem-artificial neural network techniques," Int. J. Res. -GRANTHAALAYAH, vol. 10, no. 1, pp. 69–95, Jan. 2022, doi: 10.29121/granthaalayah.v10.i1.2022.4434.

List of Further Publication of the Author

Article papers

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[2] K. Dumor and **K. Gbongli**, "Trade impacts of the New Silk Road in Africa: Insight from Neural Networks Analysis," Theory, Methodol. Pract., vol. 2021, no. 02, pp. 13–26, 2021.

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Appendix

Appendix A. Measurement scales and items (Chapter 4)

Measurement Scales
General Trust (G-trust) (Zhou, 2013)
Mobile financial services are trustworthy (G-trust1)
Mobile financial services keep their promises(G-trust2)
Mobile financial services keep customers' interests first(G-trust3)
Dispositional Trust (DTrust) (M. K. O. Lee et al., 2001)
It is easy for me to trust a person/thing. (DTrust1)
My tendency to trust a person/thing is high. (DTrust2)
I tend to trust a person/thing even though I have little knowledge of it. (DTrust3)
Trusting someone or something is not difficult. (DTrust4)
Technology Trust(TTrust) (Cheng & Macaulay, 2014)
I think the application of the mobile device for financial products or services will improve my decision on the financial transaction. (TTrust1)
I would like to try financial products such as money transfer using mobile devices application (TTrust2)
I think there is no technical risk in using mobile phone technology to access financial products. (TTrust3)
Vendor Trust (Vtrust) (Y. Fang et al., 2014)
The vendor can safeguard the interests of consumers. (Vtrust1)
The vendor hopes to maintain a good reputation. (Vtrust2)
Overall, the vendor is credible. (Vtrust3)
Perceived Risk (PRisk) (Featherman & Pavlou, 2003)
Using MFS would expose me to any kind of risk perception. (PRisk1)
When MFS users' accounts suffer from fraud, they will have a possible loss of status in a social group. (PRisk2)
Overall, due to transaction errors, there might be a loss of money with high risk. (PRisk3)
I believe that the overall riskiness of mobile financial service systems is high. (PRisk4)
Perceived Privacy Risk (PPrivR) (Jarvenpaa & Tractinsky, 1999)
The chances of using MFS and losing control over the privacy of my payment information are high. (PPrivR1)
My Personal information could be exposed or access when using m-payment. (PPrivR2)
My Privacy information might be misused, sold or inappropriately shared. (PPrivR3)
Information about my MFS transactions would be known to others. (PPrivR4)
The potential loss of control over personal information is high with MFS. (PPrivR1)
Perceived Time Risk (PTimeR) (L. Zhang et al., 2012)
Losing of Time could be caused by instability and low speed. (PTimeR1)
I might waste much time fixing payment errors if m-payment leads to a loss of convenience. (PTimeR2)
The possible time loss from having to set up and learn how to use MFS is high. (PTimeR3)
I may lose time when making a wrong procuring decision by wasting time seeking and making the purchase using MFS. (PTimeR4)
Perceived Security Risk (PSecurR) (Tsiakis, 2012)
My personal information could be collected, tracked, and analyzed. (PSecurR1)
Losing my phone might allow criminal to gain access to my MFS PIN and other sensitive information. (PSecurR2)
I think my Identity can be stolen and used to do mobile payment transaction fraudulently
MFS is one of the new useful IT applications, and I am aware of its security issues in the transactions. (PSecurR3)
If I lose the mobile phone as an MFS user, in the meantime, I could lose my e-money as well. (PSecurR4)

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To continue Appendix A. Measurement scales and items (Chapter 4)

Perceived Cost (PCost) (Luarn & Lin, 2005)
I have to pay higher costs when using MFS in comparison with other banking options. (PCost2)
Using mobile financial services is a cost burden to me. (PCost3)
It costs a lot to use mobile financial services. (PCost4)
MFS lacks promotion and other incentives according to the cost offers. (PCost5)
Adoption of Mobile Financial Services (AdMFS) (S.K. Sharma et al., 2016)
I will opt for mobile financial services anytime I have the opportunity to use it. (AdMFS1)
I would embrace mobile financial services usage. (AdMFS2)
I think adopting a mobile device for fund transfer is attractive. (AdMFS3)
I will use Mobile Financial Services for all my financial transactions. (AdMFS4)
Mobile Financial services are the newest transaction tool that I opt to use. (AdMFS5)

Appendix B. Conceptual framework of variables (Chapter 5)

Items	Measurement Scales
Mobile money self-efficacy (SEMM) (Venkatesh & Bala, 2008)	
SEMM1	It would be easy for me to learn how to use a smartphone for mobile money
SEMM2	I could use mobile money if someone showed me how to do it
SEMM4	I am able to use mobile money if there is no one around to tell me what to do.
Mobile money technology anxiety (TAMM) (J. K. Park et al., 2019) (Meuter et al., 2003)	
TAMM1	Mobile money service makes me feel uncomfortable
TAMM2	I feel apprehensive about using new technology
TAMM3	I fear that I will do the wrong thing when I use new technology
Perceived ease-of-use mobile money (PEMM) (Upadhyay & Jahanyan, 2016) (Venkatesh & Davis, 2000)	
PEMM1	MFS give people more control over their daily financial transactions
PEMM2	MFS that use the newest mobile technologies is much more convenient to use.
PEMM3	MFS gives you more freedom of mobility.
Mobile money perceived usefulness (PUMM) (Kalinic et al., 2019) (Davis et al., 1989)	
PUMM1	In general, the mobile-based payment system could be useful for me
PUMM2	I would find it useful to use a smartphone for my financial transaction
PUMM3	The mobile money service system is a useful mode of payment
Attitude toward mobile money (ATMM) (MacKenzie & Lutz, 1989) (Lafferty et al., 2015)	
	In sum, how would you classify your overall attitude towards using smartphones for m-money?
ATMM1	Negative-Positive
ATMM2	Unfavourable-Favourable
ATMM3	Poor-Excellent
ATMM4	Unattractive-Attractive
Personal innovativeness in mobile money (PIMM) (Ritu Agarwal & Prasa, 1998) (Flynn & Goldsmith, 1993)	
PIMM1	I heard about a new IT; I would look for ways to experiment with it.
PIMM2	Among my peers, I am the first one to try out new information technologies.
PIMM3	In general, I am not hesitant to try out new information technologies
PIMM4	Other people come to me for advice on new mobile technologies and services.
Attitude toward mobile money (ATMM) (Venkatesh & Davis, 2000) (Venkatesh, 2000)	
IUMM1	I intend to use/reuse mobile financial services shortly.
IUMM2	Assuming that I have access to mobile financial services, I intend to use it.
IUMM3	Given that I have access to mobile financial services, I predict that I would use it.
IUMM4	To the extent possible, I would take advantage of mobile money for my transaction activities.

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Appendix C. Conceptual framework of variables (Chapter 6)

Items	Measurement scales
	Perceived privacy risk (PPR) (C. M. Cheung & Lee, 2001) (Flavián & Guinalíu, 2006)
PPR1	I think subscribing to mobile money service (MMS) increases the likelihood of receiving spam/ spam SMS
PPR2	I think MMS providers could provide my personal information to other companies without my consent
PPR3	I think mobile money service providers will send SMS advertisement without the user's consent
PPR4	I think MMS providers endanger my privacy by using my personal information without my permission
	Perceived time risk (TIR) (Nam & Quan, 2019) (Q. Yang et al., 2015)
TIR1	I worry that it will cost me much time to access mobile money services.
TIR2	It takes time to perform transactions using mobile money service
TIR3	It takes time to solve problems with mobile money service
TIR4	I worry that it will cost me much time to confirm my ID and other details for mobile money transactions
	Perceived security risk (SER) (Q. Yang et al., 2015) (Featherman & Pavlou, 2003)
SER1	I worry that a third party will steal the transaction information.
SER2	I worry that a third party will use my account information to perform an illegal transaction.
SER3	I worry that a third party can withdraw the money I send via mobile money.
SER4	I worry that the money I send through mobile money will not reach the intended recipient.
	Perceived monetary risk (MOR) (Kuisma et al., 2007) (Fain & Roberts, 1997)
MOR1	The use of mobile money services is economical
MOR2	In my opinion, using mobile money service saves cost
MOR3	The use of mobile money services increases my ability to control my financial matters by myself
	Perceived overall risk (POR) (Featherman & Pavlou, 2003) (Roy et al., 2017)
POR1	Considering all sorts of factors combined, using mobile money service exposes me to a comprehensive risk
POR2	The mobile money service provider may not deliver the expected standard of service
POR3	I may not be able to access my account because of a poor network connection
POR4	Using mobile money service for a financial transaction would be risky
POR5	I may not get financial advantages as suggested by the mobile money service provider
	Behavioral intention to use the system (BI) (Davis, 1989) (Davis et al., 1989) (Venkatesh et al., 2012b)
BI1	I will use/continue using mobile payment services in the future
BI2	I will always try to use mobile money service in my daily life
BI3	I will likely use/continue using mobile payment services in the future
BI4	Given a chance, I predict I will use/continue using mobile payment services in the future