SOCIAL MEDIA AND MOBILE MONEY ADOPTION: COMPARATIVE EVIDENCE FROM SOUTH AFRICA AND ZIMBABWE

by

SHALLONE MUNONGO

submitted in accordance with the requirements for
the degree of

DOCTOR OF PHILOSOPHY

in the subject

MANAGEMENT STUDIES

at the

UNIVERSITY OF SOUTH AFRICA

SUPERVISOR: Professor Daniel Makina

CO-SUPERVISOR: Professor Kunofiwa Tsaurai

JUNE 2019

ABSTRACT

The study investigated the effects of social media on mobile money adoption in South Africa and Zimbabwe. The main gap identified in empirical literature is the omission of social media use in technology adoption models and social networking theories. While some theories acknowledge the role of social influences in technology adoption, the social interactions considered therein are not mediated through the internet as is social media. Furthermore, no empirical study has to date focused on how social media influences mobile money technology adoption. Thus, this study deviates from the offline social network analysis approach which is restricted to the neighbourhood effects, physical contact, cell phone calls and text messages where information on mobile money technology is disseminated to an individual's limited social circle. The secondary data used for the study were obtained from individual responses in the cross-sectional FinScope consumer surveys South Africa 2015 and Zimbabwe 2014 which were conducted and reported by FinMark Trust (2015; 2014). The study employed the binary logistic regression model to estimate the nature of effect. The results of the study indicated that use of social media had a positive and statistically significant impact on mobile money adoption in both South Africa and Zimbabwe. The results also revealed that despite there being a lower internet penetration and social media usage rate in Zimbabwe than South Africa, the use of social media in the former led to a higher rate of mobile money adoption. The study also established that mere use of social media and availability of mobile money technology did not translate to a high adoption rate; instead, availability had to be matched by a demand for the financial services. Additionally, the study found that the interaction of mobile money adoption and use of social media increased the overall mobile money adoption in both countries. The study recommended the implementation of collective policies that increase internet penetration to facilitate increased use of social media platforms and promote mobile money adoption to foster improved financial inclusion in developing countries.

Key terms: Social media; Mobile money adoption; South Africa; Zimbabwe; Financial inclusion.

ABSTRAK

Hierdie studie het die gevolge van sosiale media op die ingebruikneming van mobiele geld in Suid-Afrika en Zimbabwe ondersoek. Die belangrikste leemte wat in empiriese literatuur geïdentifiseer is, is die weglating van die gebruik van sosiale media in tegnologieaanvaardingsmodelle en sosialenetwerkvorming-teorieë. Hoewel sommige teorieë (teorie van beredeneerde handeling; teorie van beplande gedrag; diffusie van innovasie) die rol van sosiale invloede op tegnologieaanvaarding erken, word die sosiale interaksies wat daarin oorweeg word nie deur middel van die internet bemiddel nie, soos wel in die geval van sosiale media. Boonop het geen empiriese studie tot op hede gefokus op hoe sosiale media die ingebruikneming van mobielegeld-tegnologie beïnvloed nie. Hierdie studie wyk dus af van die niegekoppelde sosialenetwerkontleding-benadering, wat beperk is tot die omgewingsgevolge, fisieke kontak, selfoonoproepe en teksboodskappe, waar inligting oor mobielegeld-tegnologie aan ’n individu se beperkte sosiale kring versprei word. Die sekondêre data wat vir die studie gebruik is, is verkry uit afsonderlike response in die deursnee- FinScope-verbruikersopnames (Suid-Afrika 2015 en Zimbabwe 2014), wat onderneem en bekendgemaak is deur FinMark Trust (2015; 2014). Die studie maak gebruik van die binêre logistiese regressiemodel om die aard van effek te skat. Studiebevindings dui daarop dat die gebruik van sosiale media ’n positiewe en statisties beduidende uitwerking op die ingebruikneming van mobiele geld in sowel Suid-Afrika as Zimbabwe het. Die resultate wys ook dat, ondanks ’n laer internetpenetrasie en sosialemedia-gebruikskoers in Zimbabwe, die gebruik van sosiale media in Zimbabwe tot ’n hoër koers van ingebruikneming van mobiele geld in dié land as in Suid-Afrika tot gevolg het. Daar word verder waargeneem dat die blote gebruik van sosiale media en die beskikbaarheid van mobielegeld-tegnologie nie geredelik omgesit kan word in ’n hoë ingebruiknemingskoers nie; beskikbaarheid moet met ’n vraag na die finansiële dienste gepaard gaan. Daarbenewens toon die studie dat die interaksie tussen mobielegeld-ingebruikneming en die gebruik van sosiale media die oorkoepelende ingebruikneming van mobiele geld in albei lande versterk. Die studie beveel die implementering van beleide aan wat internetpenetrasie verhoog om wydverspreide gebruik van sosiale media te fasiliteer, wat op sy beurt die ingebruikneming van mobiele geld sal bevorder, wat finansiële insluiting sal bevorder.

Sleutelterme: sosiale media, ingebruikneming van mobiele geld; Suid-Afrika; Zimbabwe; finansiële insluiting

ISIFINYEZO ESIQUKETHE UMONGO WOCWANINGO

Ucwaningo luphenyisise imiphumela ye-social media ekwamukelweni kwe-mobile money eNingizimu Afrika naseZimbabwe. Igebe elikhulu eliphawuliwe kwimibhalo yobufakazi ukweqiwa kokussetshenziswa kwe-social media ekwamukelweni kwama-technology adoption models kanye namathiyori e-social networking. Kodwa amanye amathiyori (i-theory of reasoned action; i-theory of planned behaviour; i-diffusion of innovation) amukela indima yemithelela ye-social influences ekwamukelweni kwetheknoloji, ngokusebenzisana kwama-social interactions abonelelwe lapha, awaxhunyaniswa nge-inthanethi, njenge-social media. Kanti-ke futhi okunye, akukho bufakazi bocwaningo kuze kubemanje obugxile kwindlela i-social media enomthelela ngayo kwi-mobile money technology adoption. Ngakho-ke, lolu cwaningo luyehluka kwizinqubo ze-offline social network analysis approach, enezihibe kwimiphumela esondelene nayo, ukuxhumana ngokubamba, ukushayelana izingcingo nge-cellphone, kanye nemilayezo ebhaliwe, lapho ulwazi kwi-mobile money technology lusatshalaliswa kumuntu ngamunye nalabo asondelene nabo. I-secondary data esetshenzisiwe kucwaningo itholakale kwizimpendulo zabantu ngamunye kwi-cross-sectional FinScope consumer surveys (iNingizimu Afrika 2015 kanye neZimbabwe 2014), olwenziwa nokubikwa nge-FinMark Trust (2015:2014). Ucwaningo lusebenzisa i-binary logistic regression model ukulinganisa inhlobo yomphumela. Imiphumela yocwaningo ikhombisa ukuthi i-social media inomphumela omuhle futhi ngomphumela wezibalo ezibalulekile ekwamukelweni kwe-mobile money okwamukelwe kuwo womabili amazwe iNingizimu Afrika kanye neZimbabwe. Imiphumela ikhombise nokuthi, ngisho noma i-inthanethi ingakangeneleli kangako kwezinye izindawo, kodwa izinga lokusetshenziswa kwe-social media eZimbabwe kungaphezulu kuneNingizimu Afrika, ukusetshenziswa eZimbabwe kuhola phambili ngezinga eliphezulu ekwamukelweni kwe-mobile money kunaseNingizimu Afrika. Kanti futhi kuphawulwa ukuthi ukusetshenziswa kwe-social media kanye nokutholakala kwe-mobile money technology, akuhambelani ngezinga lokwamukelwa kakhulu; ukutholakala kumele kuhambelane nesidingeko samasevisi ezezimali. Nangaphezu kwalokho, ucwaningo lukhombisa ukuthi ukusebenzisana kokwamukelwa kwe-mobile money nokusetshenziswa kwe-social media kuphakamisa ukwamukelwa kakhulu kwe-mobile money kuwo womabili amazwe. Ucwaningo luncoma ukuthi ukwamukelwa kwemigomo enyusa ukungenelela kakhulu

kwe-inthanethi ukulekelela ukusetshenziswa kakhulu kwe-social media, kanti futhi lokhu okuzophakamisa kakhulu ukwamukelwa kwe-mobile money okusiza ukubandakanya wonke kwezezimali.

Amathemu abalulekile: i-social media, i-mobile money adoption; iNingizimu Afrika; iZimbabwe; ukubandakanya uwonke kwezezimali

ACKNOWLEDGEMENTS

My heartfelt appreciation goes to the following:

(1) The Lord God Almighty for the strength and all provisions required for such a feat.

(2) My supervisors, Professors Daniel Makina and Kunofiwa Tsaurai for their guidance, timely and thorough reviews, feedback, patience and immense support, without which completion of this thesis would have been an insurmountable task.

(3) The University of South Africa for funding the PhD study program - I am forever grateful.

(4) FinMark Trust for granting permission to use the FinScope South Africa 2015 and Zimbabwe 2014 data sets, without such assistance the study would have been impossible.The findings, interpretations, and conclusions expressed in this thesis are entirely those of the author.

(5) Great Zimbabwe University (GZU) for granting leave of absence to undertake PhD studies.

(6) Friends and colleagues from the Department of Banking and Finance and Faculty of Commerce (GZU) for their unwavering support and unknowingly sharing insightful ideas, all which contributed meaningfully to this thesis.

(7) My family for all their financial support, encouragement, understanding and prayers.

DEDICATION

I dedicate this thesis to my beautiful daughters - Kayla and Janelle Munongo. Your incredible encouragement, patience and prayers strengthened me throughout the challenging journey.

DECLARATION

Name:	Shallone Munongo
Student number:	57638756
Degree:	Doctor of Philosophy in Management Studies
Title:	Social media and mobile money adoption: Comparative evidence from South Africa and Zimbabwe.

I declare that the above thesis is my own work and that all the sources that I have used or quoted have been indicated and acknowledged by means of complete references.

S. Munongo	19 June 2019
SIGNATURE	DATE

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

LIST OF ABBREVIATIONS

3G	Third Generation
4G	Fourth Generation
AfDB	African Development Bank
CENFRI	Centre for Financial Regulation and Inclusion
DFID	Department for International Development
DOI	Diffusion of Innovation
DTPB	Decomposed Theory of Planned Behaviour
ECDL	European Computer Driving Licence
FITS	Financial Inclusion Tracker Surveys
G2P	Government-to-Person
GSMA	Groupe Speciale Mobile Association
ICT	Information Communications Technology
IMF	International Monetary Fund
ITU	International Telecommunication Union
MMA	Mobile Money Adoption
MNO	Mobile Network Operator
OECD	Organisation for Economic Co-operation and Development
P2P	Person-to-Person
PCA	Principal Component Analysis
POTRAZ	Postal and Telecommunications Regulatory Authority of Zimbabwe
RBZ	Reserve Bank of Zimbabwe
SADC	Southern African Development Community
SCT	Social Contagion Theory
SLT	Social Learning Theory
SSA	Sub-Saharan Africa
Stats SA	Statistics South Africa
SWT	Strength of Weak Ties Theory
TAM	Technology Acceptance Model
TPB	Theory of Planned Behaviour

TRA	Theory of Reasoned Action
USA	United States of America
UTAUT	Unified Theory of Acceptance and Use of Technology
ZIMSTAT	Zimbabwe National Statistics Agency

CHAPTER 1

INTRODUCTION AND BACKGROUND

1.1 INTRODUCTION

Financial inclusion, the access to and usage of formal financial products by all is crucial for developing economies to realise poverty reduction and ensure equality of access to financial markets and resources (Demirgüç-Kunt et al., 2018; Donovan, 2012). FinMark Trust (2014:4) defines the financially excluded as the adult population segment who do not have or use any financial products and or services, whether formal or informal. The goal of realising financial inclusion involves paying specific attention to those segments of the populace that have traditionally been excluded from or under-served by the formal financial services' providers. To this effect, the African Development Bank (AfDB, 2013) notes that financial inclusion entails more than the provision of formal accounts and credit facilities - it includes improved access to savings, payments, risk management products and affirmative consumer rights' protection.

Subbarao (2009) notes that financial inclusion is a precursor for sustaining equitable growth in any economy because it is a means of channelling the savings of the poor into formal financial intermediation and redirecting them towards meaningful investments. Without access to formal savings, payments, credit and insurance, the financially excluded people must rely on informal risky and exorbitant means which often drive them into deeper poverty. In response, resilient action on accelerating financial inclusion is urgently required as growing literature indicates that financial inclusion feeds into broader and stronger economic development, together with deeper financial intermediation (International Monetary Fund, 2016).

Studies have found that when people use formal financial services, they are more capacitated to undertake and grow entrepreneurial ventures, absorb or manage risks and avoid the clutches of the usurious money lenders (Zhang and Posso, 2017; Cull, Ehrbeck and Holle, 2014; Dupas and Robinson, 2013a). However, despite the aforementioned benefits of financial inclusion, the 2017 Global Findex Database report by Demirgüç-Kunt et al. (2018) indicates that 1.7 billion adults worldwide remain excluded from rudimentary financial services. Further analysis of the financially excluded reveals disparities among the youths, females, those living in rural peripheries and the poor. In addition, the 2017 Global Findex Database report reveals that in most parts of the world, the financial inclusion level for women continues to fall short than that of men - 65 percent of women globally own formal bank accounts paralleled with 72 percent of men; a variance of 7% which has been constant from 2011. The gap in formal bank account ownership between the rich and the poor has not narrowed since 2014 either: on average globally, poorer adults are less likely than wealthier ones to own a formal bank account. Moreover, urban populations continue to benefit from a wider selection of financial services than the rural populace.

Statistics from the World Bank (2015) indicate that Africa is the world's second largest and most populous continent, with 1 billion people spread across 56 countries. There is considerable variation in bank account ownership within Africa, where 24% of the adult population in the Sub-Saharan Africa (SSA) region are reported to own a formal account. Account penetration varies from 51% for Southern Africa, 11% for Central Africa and 20% for North Africa (ibid). Sub-Saharan Africa has an under-banked but financially active population. The vastness of Sub-Saharan Africa's surface area of 24 million square kilometres, combined with poor infrastructure, makes it difficult to for conventional banks to expand physical branch networks. The widely dispersed and often inaccessible rural peripheries limit economies of scale for the traditional physical branch banking model. Also, factors such as the lack of or low and erratic income relative to costs, the lack of documentation, credit history, long distances to the nearest bank branch, poor product design, narrow product range, distrust in the financial system, low levels of educational attainment, religious concerns and financial illiteracy combined dissuade many in Sub-Saharan Africa from using the formal financial services (Demirgüç-Kunt et al., 2018; Aron, 2017; Donovan, 2012; Jack and Suri, 2014).

1.2 OVERVIEW OF MOBILE MONEY ADOPTION

The current mobile phone revolution, spurred by falling device prices, is actively transforming the lives of many in developing economies. The Groupe Speciale Mobile Association (GSMA, 2015) notes that the mobile communications sector in the Sub-Saharan African region has undergone rapid growth, with a mobile phone penetration rate of 77% reported in 2015, and estimated to rise to 93% by 2020. FinMark Trust (2016) reports that the growth in telecommunications penetration rates suggests that in some developing economies, there is a higher ownership of cell phones than other basic amenities such as electricity, clean water or a bank account. Studies observe that information technology advancements in developing economies are thus providing not merely a communication means - they are also furthering financial inclusion through mobile money platforms (Ammar and Ahmed, 2016; Demombynes and Thegaya, 2012).

Currently, there are several definitions of the concept mobile money. Jenkins (2008) defines mobile money as a financial service obtainable through use of a mobile device. Tobbin and Kuwornu (2011:2) submit that mobile money comprises of the various ingenuities such as long-distance remittances, micro-payments, and informal air-time bartering schemes directed towards delivering formal financial services to the financially excluded through mobile technology. GSMA (2015:16) describes mobile money as the use of “information and communication technologies and non-bank retail channels to extend the delivery of financial services to customers who would otherwise not be reached profitably by means of the traditional bank branch-based financial services in a profitable way”.

Di Castri (2013) identifies several distinct features of the numerous descriptions of mobile money technology. Firstly, mobile money is electronic money dispensed upon receiving of funds in an equivalent amount to the obtainable financial worth. Secondly, mobile money is electronically stored on a mobile phone and is readily convertible to cash. Thirdly, mobile money can be seamlessly used as a means of transacting by additional persons other than the issuer - for instance in retail payments, government-to-person (G2P) transfers, business transfers, person-to-person transfers (P2P) and donor-to-person cash transfers. Fourthly, the mobile money balance is supported by the storage of equivalent funds in a banking institution, subject to a country's financial regulations.

Lal and Sachdev (2015) and Chitungo and Munongo (2013) note that mobile money services are usually delivered by a mobile network operator (MNO), a financial institution (typically a bank), or a joint initiative between the two parties. Ammar and Ahmed (2016) and Lal and Sachdev (2015) found that the MNO-led model is most popular in developing countries because mobile network operators leverage on their ownership of telecommunications infrastructure, having immediate access to consumers' cell phones and a well-established physical presence in peripheral geographies. However, Lal and Sachdev (2015) report that the MNO-led model's shortcoming is that the MNOs usually have neither familiarity in developing or distributing financial services, nor the regulatory capability to do so. Consequently, the MNOs resort to joint efforts with banks since the latter have the advantage of delivering comparable services to the financially included populace (ibid). In return, a partnership with an MNO to deliver mobile money services enables the banking institutions to adopt scalable business models that cost-effectively envelope the lower income financially excluded communities into the formal system.

Demirgüç-Kunt et al. (2018) revealed that 2% of global adults used mobile money technology in 2014, with Sub-Saharan Africa leading the world at 12%. While most adopters in the region were largely concentrated in East Africa in 2014, presently, mobile money account ownership has spread to West Africa and beyond. Interestingly, Demirgüç-Kunt et al. (2018) note that Sub-Saharan Africa is home to all the ten countries worldwide in which the number of adults who own mobile money accounts surpasses those with an account at a financial institution: Burkina Faso, Chad, Côte d'Ivoire, Gabon, Kenya, Mali, Senegal, Tanzania, Uganda, and Zimbabwe. Mobile money accounts are most popular in Kenya where 73% of adults have them, and in Uganda and Zimbabwe where 50% of the adult population has adopted the financial innovation (ibid). Elsewhere in Africa, the 2017 Global Findex Report reveals that mobile money account in Burkina Faso, Côte d'Ivoire, and Senegal is 33%, 39% in Ghana, and 45% Gabon and Namibia.

While mobile money adoption is common in Sub-Saharan Africa, Demirgüç-Kunt et al. (2018) reveal that the financial innovation has also been taken up in other parts of the world including Haiti (14%), Bangladesh (21%), Chile (20%), Turkey (16%), and Paraguay (29%). Although the overall proportion of mobile money account ownership in the Sub-Saharan African region doubled between 2014 and 2017, its impact on financial inclusion among individual economies however varies. Some countries - Côte d'Ivoire, Tanzania and Uganda gained marginal increases, others - Burkina Faso, Gabon, Ghana, and Senegal experienced significant rises, while Kenya, Zambia, and Zimbabwe recorded the largest growth rates in mobile money adoption (ibid). Notwithstanding the differences, the results suggest that mobile money adoption is an effective means to reduce financial exclusion in developing countries.

In addition to accelerated financial inclusion, empirical literature provides numerous other benefits provided by mobile money adoption, including improved household welfare, increased savings and risk sharing (Jack and Suri, 2014; Demombynes and Thegeya, 2012; Donovan, 2012; Di Castri, 2013). In Tanzania and Uganda, Moshy and Mukwaya (2011) have found evidence that mobile money services enable rural communities usually overlooked by the mainstream banking system to access much needed formal financial services. Similarly, Peruta (2018) observes that the vast network of mobile money service agents in the remote peripheries counters physical bank presence, thereby conveniently providing much-needed financial services to all.

The GSMA (2017) found that for customers, mobile money technology provides a safer, more efficient and more convenient payment option than cash, thereby saving travel time and costs and reducing the risk of theft (GSMA, 2017). Likewise, in Zimbabwe, Mago and Chitokwindo (2014) reported that reduced transport costs, affordability, easy access to cash, convenience, low transaction costs, wider reach to unbanked areas and access to credit and improved living standards were the merits of mobile money services' adoption. Thus, mobile money adoption facilitates greater financial intermediation of the entire economy since financial deepening stimulates demand for formal financial services across the populace (ibid). Kikulwe et al. (2014) concluded that in Kenya, adoption of mobile money technology had a positive impact on household income through three main pathways – the receipt of higher remittances, greater farming intensity and profits, and a higher degree of commercialization of banana farms. Munyegera and Matsumoto (2014) and Murendo et al. (2015a; 2015b) established that the adoption of mobile money services in rural Uganda increased household per capita consumption owing to increased remittances. Likewise, Aker et al. (2011) reported significant increases in Kenya in the types of food and non-food items and the diversity of diet consumed by adopter households.

Furthermore, Suri et al. (2012), Jack, Ray and Suri (2013), Blumenstock et al. (2014), and Murendo et al. (2015a; 2015b) reported that in Kenya, the adoption of mobile money technology improved how households responded to risk exposures. The studies note that the use of mobile financial services enabled family members and friends to swiftly transfer money to a recipient's mobile phone by sending a simple text message. Despite the possibility of misappropriation, mobile money services are much safer than most informal means of cash transfer (ibid). Similarly, a Financial Inclusion Tracker Survey (FITS) project of 2,980 households in Tanzania conducted and reported by Intermedia (2013) found that households with mobile money adopters utilised a wider range of financial products such as insurance and savings when compared to non-adopter households.

The use of mobile money technology also facilitates farmers' assimilation into a critical high-value supply chain network. Rao and Qaim (2011) reported that in Kenya, product sales to retailers are frequently accompanied by payment delays - a challenge that could be easily mitigated by use of mobile money transfers. Therefore, adoption of mobile money technology significantly can reduce the market turnaround time for the smallholder farmers, and facilitate positive employment effects since labourers can also be remunerated paid using mobile money platforms. Ultimately, adoption of mobile money technology then leads to higher economic activity as more productive time is efficiently utilised.

Literature also reports that the adoption of mobile money technology creates direct job and entrepreneurial opportunities for many people employed as mobile money agents, thereby stimulating economic development (Communications Commission of Kenya, 2013; Jusilla, 2015). Demombynes and Thegeya (2012) and Mbiti and Weil

(2011) found that in Kenya the adoption of M-Pesa culminated in the growth of formal savings. Similarly, Batista and Vicente (2013) reported that use of the Mkesh platform in Mozambique increased savings rates. In Afghanistan, Blumenstock et al. (2015) observed that employees who received their salaries through the M-Paisa mobile money platform were more likely to formalise a greater proportion of their savings.

Mobile money technology usage is also associated with lower transaction costs than conventional banking and informal means. In a study which compared 26 banks internationally, McKay and Pickens (2010) concluded that mobile money services were on average 19 percent cheaper than conventional banking. Similarly, Aker et al. (2011) reported that in Niger the use of the Zap mobile money platform for social grants' transfers reduced funders' distribution costs in two ways. Firstly, the study notes that cash transfers were 30% more costly for funders than using Zap. Secondly, Aker et al. (2011) report savings owing to mobile money adoption- individuals in Zap-adopter villages had a cost saving equivalent to 30 minutes per transfer when compared with the non-adopter villages.

1.3 OVERVIEW OF SOCIAL MEDIA USE

Presently, there is no one universally accepted definition for the term social media. Strauss and Frost (2011) define social media as a form of media that is premised on online dialogues between people. Hayta (2013) describes social media as the online networking podia which enable people to exchange information, thoughts or interests. From another perspective, Brown (2009) in Rehman et al. (2014:1) refers to social media as a "web-based site which brings different people together in a virtual platform and ensures a deeper social interaction, stronger community and implementation of cooperation projects". Similarly, Kahraman (2010) outlines social media to be online fora used by people to disseminate information among each other.

Garrido-Moreno and Lockett (2016), Hansen et al. (2011), Jashari and Rrustemi (2017) and Berthon et al. (2012) note that currently, there are various types of social media platforms, such as blogs, microblogs (Twitter, Tumblr, Posterous), social networks (Facebook, Google Plus, Cafe Mom, Gather, Fit sugar, LinkedIn), personal broadcasting tools (Blog Talk radio, Ustream, Livestream), collaboration tools (Wikipedia, Wikitravel, Wikibooks), video sharing sites (YouTube, Vimeo, Viddler), media sharing (Instagram, YouTube, Flickr), social news and bookmarking (Digg, Reddit), rating and review pages (Yelp, Amazon ratings, Angie's List), publishing tools (WordPress, Blogger, Square space), virtual Worlds (Second Life), and group buying (Groupon, Living Social, Crowdsavings). Zorlu (2011) highlights the point that in order to classify a web site or application as social media, it should have autonomous users or members, be free of time and geographical restrictions, permit user-based content, and assure interaction between users.

Strauss and Frost (2011) observed that the main distinction between social media and traditional media is that in the former, communication does not follow a one-way model - rather, it entails an interactive dialogue format where anyone can upload, discuss, edit and rate others content. The latter includes print media, which delivers information to many subscribers, or a radio station that broadcasts the same programmes to an entire city. Compared to traditional media, Hayta (2013) noted that social media have an impact on a wider audience, at a greater pace, increased regularity, usability, timeliness and longevity. Subsequently, social media have become an essential tool in the dissemination of information.

The use of social media has emerged as an effective present-day means of communication in real-time. Khatib (2016) and Smith and Zook (2011) reported that social media platforms had changed the communications landscape – they facilitate instantaneous diffusion of essential information across large online audiences, with a potentially viral effect. Furthermore, individuals can now recognise new needs on social media when surfing on social networks such as Facebook; here they obtain friends' comments, shares, likes or tweets about certain brands, products, or services. Therefore, social media enables users to review products and share their recommendations, opinions experiences to a vast audience and in turn influence other individuals within their social networks on a greater scale through their online interactions. Growing empirical literature shows that social media impacts on financial behaviour such as general purchasing, investing, savings and crowdfunding success (Nyagucha, 2017; Kosavinta et al., 2017; Kavitha and Bhuvaneswari, 2017; Ammann and Schaub, 2016; Makina, 2017; Beier and Wagner, 2015).

The International Telecommunication Union (ITU, 2015) reported that more than three billion people worldwide use the internet, a sharp increase from 778 million recorded in 2000. Global social media penetration is also on the rise - Statista (2017) notes that 2.46 billion of internet users are social media users. This is a phenomenal increase from 970 million reported in 2010, with the figures projected to rise to 2.77 billion in 2019. These increases in global social media use are attributed mainly to the worldwide use of cheaper smartphones, other mobile devices and the internet, which in turn have facilitated social network interactions. GSMA (2015) found that the internet or broadband penetration rate for Sub-Saharan Africa was 24% in 2015, and is projected to reach 93% in 2020. Furthermore, migration to higher third and fourth generation (3G and 4G) speed network connections and increased ownership of smartphones in the region remain swift, with mobile internet penetration anticipated to rise from slightly above 20% recorded in 2015 to nearly almost 60% in 2020 (ibid). As a result of these technological advancements, GSMA (2018) established that internet connectivity is now prime means of accessing life-enhancing information many in Sub-Saharan Africa.

Eldridge (2016) in huffpost.com (2017) reported that social media are quickly altering the operations of the financial services industry. Online platforms such as WeChat and Viber in Asia and Facebook the world over have shifted focus from mere social connections to active delivery of a wide range of formal financial services to patrons either directly or through partnerships. Also, social media are being utilised by governments and service providers as a low cost, far reaching tool to improve financial inclusion levels in developing economies. The Centre for Financial Regulation and Inclusion (Cenfri, 2016) found that in order to spread to the most vulnerable, rural and hard-to-reach financially excluded masses in Cambodia, the country's central bank had launched a financial services awareness campaign to encourage inter-generational dialogue by engaging the social media connected youth as a channel for diffusion of campaign messages. The digitally connected individuals were also encouraged to spread the information obtained through their social media networks using the traditional social network such as physical interactions in a drive to increase the adoption of formal financial services (ibid). The current study thus builds on empirical literature on social media, mobile money and financial behaviour to explore how online social interactions can be leveraged on to spread information on mobile money technology, encourage adoption and accelerate financial inclusion in developing countries.

1.4 STATEMENT OF THE PROBLEM

It is widely recognised in literature that financial inclusion is an indispensable tool in poverty reduction and accelerating inclusive economic growth (Demirgüç-Kunt et al., 2018; FinMark Trust, 2016; Donovan, 2012). Financial exclusion is high in developing countries as reported by the Global Findex Database 2017 report indicating that bank account ownership is widespread in high-income OECD economies (94%) compared to 63% in developing countries. In response, many national governments and central banks across the world have embraced policy guidelines directed towards improving financial inclusion efforts since the 2011 Maya Declaration. The subsequent financial inclusion initiatives implemented to date by national governments and central banks include the introduction of low cost, no frills bank accounts (for example the Mzansi account in South Africa), rural banks and agency banking and mobile money platforms (GSMA, 2018; Demirgüç-Kunt et al., 2018; Chitungo and Munongo, 2013; Jack and Suri, 2013). Notwithstanding the commendable progress currently realised through various financial inclusion initiatives, the 2017 Global Findex Report reveals that 1.7 billion adults worldwide remain financially excluded, a number that is too significant to ignore.

Although mobile money technology has emerged as a potent avenue for improving financial inclusion in developing economies especially Sub-Saharan Africa, its actual adoption globally is still slow at 2% (Demirgüç-Kunt et al., 2018; Kiconco et al., 2018; GSMA, 2016). The slow adoption is because the financially excluded people are unaware of, or uncomfortable with using mobile money platforms (World Bank, 2014; IMF, 2016; Murendo et al., 2015a; 2015b; Di Castri, 2013). For instance, potential adopters need to be informed of, and understand how the mobile money platforms work, the various services offered, how secure they are and what course of action to undertake to do if something goes wrong (Klapper and Singer, 2017; Zimmerman, Bohling and Rotman-Parker, 2014). Without such crucial knowledge, non-adopters remain sceptical of mobile money services, adoption is stifled which in turn adversely impacts on country-specific and global financial inclusion goals and poverty is exacerbated. On the other hand, literature has established the potency of social media in the diffusion of information and subsequently triggering financial behaviour among network members (Makina, 2017; Amman and Schaub, 2016; Khatib, 2016; Heimer, 2016, Kavitha and Bhuvaneswari, 2017). However to date, the influence of social media on the adoption of mobile money technology remains unknown. This creates a gap in our understanding of how the adoption of mobile money is influenced by the online social interactions.

1.5 OBJECTIVES OF THE STUDY

The study placed focus on the following objectives:

1. To investigate the effect of social media on mobile money adoption in South Africa and Zimbabwe.

   Theory suggests that people who use social media are more likely to be influenced by other online social network members' ideas, product and or service experience reviews (Barhemmati and Ahmad, 2015). The use of social media provides external stimulus to people to recognise a need, and consequently triggers financial behaviour (Nyagucha, 2017; Kosavinta et al., 2017; McCormick and Livett, 2012). Jashari and Rrustemi (2017), Heimer (2016), Mudholkar and Uttarwar (2015), Ammann and Schaub (2016), Makina (2017), Beier and Wagner (2015) and Bains et al. (2014) among others have empirically established that social media have a strong positive impact on financial conduct such as general purchasing, investment and crowdfunding decisions. The theoretical and empirical evidence therefore implies that online social networking interactions are linked to the spread of information about, and the adoption of mobile money services.

2. To compare the impact of use of social media on mobile money adoption in South Africa and Zimbabwe.

1.6 JUSTIFICATION FOR THE STUDY

This section spells out the motivation for carrying out a research of this nature. The study was undertaken in order to address the global contemporary issue of improving current financial inclusion levels in developing countries through the adoption of mobile money technology. The literature abounds with research on the determinants of mobile money adoption in developing economies (Masinge, 2010; Donovan, 2012; Kirui et al., 2012; Murendo et al., 2015; Chitungo and Munongo, 2013; Matsumoto and Munyegera, 2014). In addition, empirical literature on technology acceptance theories such as the Theory of Planned Behaviour (Ajzen, 1991), Decomposed Theory of Planned Behaviour (Taylor and Todd, 1995), Diffusion of Innovation (Rogers, 1995; 2003) and the Technology Acceptance Model (Davis, 1989) acknowledges the role of social influences. However, the impact of such social influences on mobile money adoption is rarely explored in isolation. Subsequently, there is a gap in our understanding of how the adoption of mobile money is driven by the social context in which users are embedded.

Furthermore, literature indicates that informal sources such as social network ties represent an important means for the acquisition of information about novel financial services and products in developing economies (Alatas et al., 2016; Giné, Karlan and Ngatia, 2014; Di Falco and Bulte, 2013; Reich, 2015; Walther, 2015). In developing countries, little evidence of this emerges from East Africa (Murendo et al., 2015a; 2015b; Kikulwe et al., 2014; Matsumoto and Munyegera, 2014; Lasserre, 2015; Fafchamps et al., 2017). However, these studies focus on offline social networks that are limited to physical contact, neighbourhood effects, cell phone calls and text messages. Consequently, these offline social networks are narrowly focused and have a limited reach of information - diffusion and adoption of mobile money technology are restricted to one’s immediate social circle. Reviewed literature for the purpose of this study indicate that no particular study has attempted to explore the impact of social media on mobile money technology adoption, despite evidence that social media influence financial decision-making (IBM Software, 2012; Kirakosyan, 2015; Knudsen, 2015).

Therefore, the impact of social media on the decision to adopt mobile money technology largely remains unexplored territory. In response and in contrast to prior studies that have paid attention to the general drivers of mobile money adoption, the current study takes a novel approach. It focuses on the impact of social media as a present day means of communication on mobile money adoption. The study also diverges from the literature in that it is comparative in nature; it provides evidence on mobile money adoption from two developing economies - South Africa and Zimbabwe which are strikingly different in terms of financial inclusion, internet penetration and social media usage levels. In addition, the study focuses on the rural and urban divides in the two countries, unlike early, closely-related research that has focused on one location (Murendo et al., 2015a; 2015b, Lasserre, 2015; Fafchamps et al., 2017; Kikulwe et al., 2014; Munyegera and Matsumoto, 2014).

The findings of the current study are relevant to governments, service providers and financial inclusion advocacy institutions. It is in the global and country-specific interests to promote financial inclusion especially in developing economies through financial technology such as mobile money. The ensuing benefits include faster economic growth, improved household welfare, increased savings, risk sharing and poverty alleviation (Demirgüç-Kunt et al. 2018; Jack and Suri, 2014; Demombynes and Thegeya, 2012; Donovan, 2012; Di Castri, 2013). The findings and recommendations of the present study will enlighten policy makers of the potency of social media in driving financial inclusion, and will take a cue on the formulation and implementation of pro-internet access and social media usage strategies. Consumers who are adequately informed on mobile money technology through social media are more likely to be capacitated to use their online social networks as avenues of further spreading knowledge on the financial innovation. To this end, the MNOs are provided an insight to upscale their operations, leverage on economies of scale to ensure affordable internet services, increase their share of the mobile money market. Overtime, the collective efforts from all these stakeholders will realise significant improvements in financial inclusion.

1.7 STRUCTURE OF THE THESIS

The remainder of the thesis is structured as follows:

Chapter 2: Theories of technology adoption and social networking

The chapter provides an in-depth discussion of the literature relating to technology adoption and social networking. It explores the theoretical background to technology adoption and social networking and examines the empirical evidence from prior studies while outlining the gap to be filled by the current study.

Chapter 3: Social media and financial behaviour

The chapter discusses the theoretical literature on social media. A critical assessment of how empirical literature on the social media–financial behaviour nexus is linked to mobile money adoption is made and the deficiencies in existing literature are highlighted.

Chapter 4: Research methodology

This chapter provides a critical review of the methodologies that have been applied in previous closely-related studies with a view to setting the context for the appropriate methodology for the study. It explains and justifies the research design used in the study. The chapter also touches on the variables, their proxies and sources of secondary data used in the study. Mindful of the various approaches that have been used in other closely-related studies on social networking and mobile money adoption, the chapter explains the econometric approaches employed to examine the social media-mobile money adoption nexus and highlights the different diagnostic tests used in addressing the study objectives.

Chapter 5: Preliminary results

The chapter focuses on the preliminary findings of the study from descriptive analysis. It provides comparisons between South Africa and Zimbabwe based on variations in social media use, mobile money adoption and the probable link between them.

Chapter 6: Estimation and empirical results

This chapter presents the outcomes from the econometric approaches applied in the study. It highlights findings from principal component analysis, binary logistic, binary probit modelling, and the diagnostic tests of the data. The results are discussed, synthesised and substantiated by theory and findings from other empirical studies.

Chapter 7: Conclusions, recommendations and suggestions for further research

The chapter summarises the findings of the study and draws conclusions from them. Recommendations to stakeholders are also made in the chapter. The chapter also acknowledges the limitations of the study and suggests areas for further study.

CHAPTER 2

THEORIES OF TECHNOLOGY ADOPTION AND SOCIAL NETWORKING

2.1 INTRODUCTION

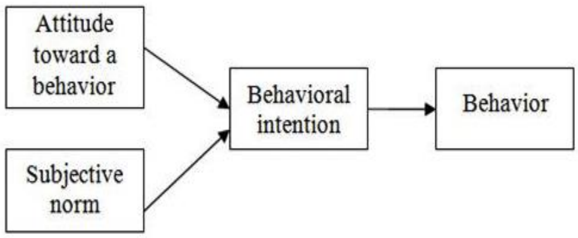
The main purpose of this chapter is to discuss the theories underpinning technology adoption and social networking. The gaps in the existing literature are emphasized and the contribution made by the current study is explained. The chapter proceeds as follows: Section 2.2 discusses the theoretical and empirical literature on technology adoption. Section 2.3 covers the theoretical and empirical perspectives of social networking that are applicable to the current study while section 2.4 concludes the chapter.

2.2 THEORIES OF TECHNOLOGY ADOPTION

Hall and Khan (2003) define technology adoption as the decision to obtain and use a novelty. Hussain (2013:2) notes that numerous theoretical views have been coined over time in an attempt to account for why people undertake technology adoption choices. Six technology adoption theories were examined in this study, namely: the theory of reasoned action, the technology acceptance model, the theory of planned behaviour, the decomposed theory of planned behaviour, the diffusion of innovation model and the unified theory of acceptance and use of technology.

The theory of reasoned action (TRA) was proposed by Ajzen and Fishbein (1975) and is grounded in a social psychology setting. It comprises attitude, subjective norms and behavioural intention as the constructs influencing adoption behaviour. Ajzen and Fishbein (1975) view attitude as the overall sentiment of people about the attractiveness or otherwise of a certain subject or conduct. Subjective norms are described as an individual's perception of significant people's views about behaving in a certain manner. According to the theory of reasoned action, attitude and subjective norms determine the behavioural intention, which in turn will be transformed into actual behaviour if the drive to behave in a specific manner is strong enough. Therefore, an individual who strongly believes that a positive outcome will result performing a particular action will have a positive attitude towards that behaviour. Conversely, if a person strongly believes that a particular behaviour will result in an adverse outcome, he or she will develop a negative attitude towards that behaviour. The theory of reasoned action is illustrated in Figure 2.1 below.

Figure 2.1: Theory of Reasoned Action



Source: Ajzen and Fishbein (1975)

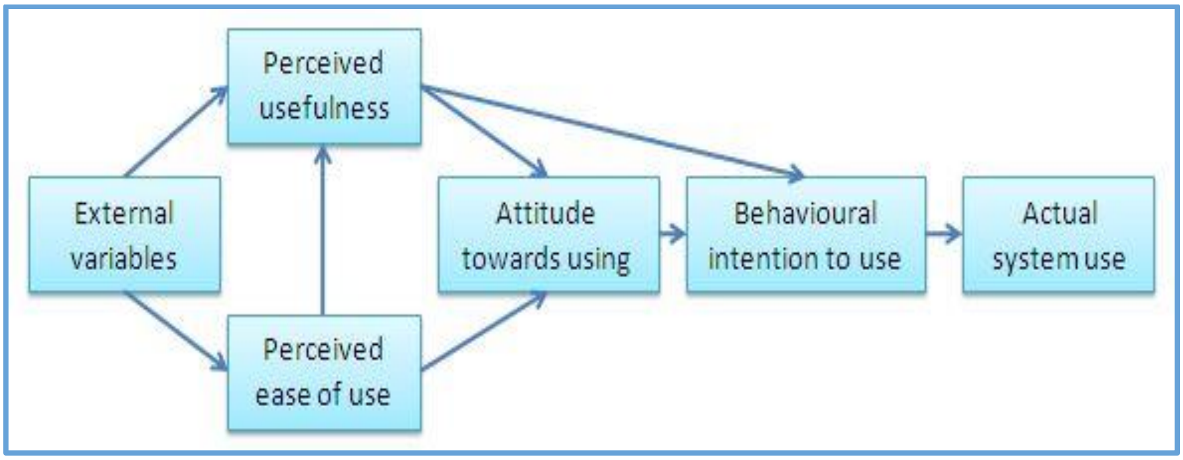
The theory of reasoned action is lauded by Davis et al. (1992) to be a firm foundation for all subsequent technology adoption theories. In line with the model, empirical studies have reported that subjective norms profoundly influenced consumers' intentions to take up mobile financial services in China (Zhou, Lu and Wang, 2010), in Somalia (Ali and Dhaha, 2013; Sayid, Echchabi and Aziz, 2012), in the United Arab Emirates (Aboelmaged and Gebba, 2013), and in Jordan (Mashagba and Nassar, 2012). The results from these studies indicated that generally, the theory of reasoned action is readily applicable to a mobile money adoption context.

The theory of reasoned action is, however, not without its shortcomings. Yusuf and Derus (2013) criticise the theory as it overlooks an individual's ability to control his or her own behaviour. Secondly, the theory of reasoned action fails to exhaustively incorporate other constructs considered relevant to mobile money adoption. The model does not take into account demographic and contextual factors that influence mobile money adoption, such as age, gender, perceived risks, relative advantages, costs, location of user (rural or urban) among others. Also, although the model acknowledges the role of the subjective norms in influencing a person's behaviour, such influences are however restricted to the traditional physical interactions amongst one's circle of family and friends, where there is a limited and slow reach of information. Thus, the theory of reasoned action model overlooks social media effects in technology adoption.

Montano et al. (2008) and Ajzen (1991) condemn the model for being exclusively restricted to predicting behaviours that are within a person's volitional control, yet in reality is not the case. Interestingly, Ajzen and Fishbein (1975) reported that their theory was only suitable for assessing individuals who were considered "rational actors". However, this view does not hold when applied to real life scenarios; humans have a strong inclination to act irrationally. Other studies (Ajzen and Fishbein, 1980; Montano et al. (2008) have discounted the theory as it results in bias owing to poor selection of participants for focus groups. Therefore, the model fails to adequately account for adoption behaviour in a mobile money services context as it omits other numerous economic and demographic variables.

The technology acceptance model (TAM) was developed by Davis (1989) to explain the acceptance of technological advancements in information systems (IS). The model is an adaptation of the theory of reasoned action, identifying the causal relationship between its two main constructs - perceived ease of use and perceived usefulness, together with attitude, behavioural intention and the actual use of technology. The technology acceptance model is displayed in Figure 2.2 below.

Figure 2.2: Technology Acceptance Model



Source: Davis (1989)

Davis (1989) describes perceived usefulness as the degree to which individuals believe that using a particular system or technology will enhance their task performance. On the other hand, perceived ease of use is the degree to which an individual believes that that using a particular system does not require physical and mental effort. According to Davis (1989), the use of technology is subject to a user's behavioural intention, and the behavioural intention is in turn influenced by attitude towards use and perceived usefulness. The attitude is itself subject to the perceived usefulness and perceived ease of use constructs. Furthermore, perceived usefulness is determined by perceived ease of use construct - the less complicated a particular system is, the more it is perceived to be beneficial to the user.

Even though the technology acceptance model was initially proposed to account for the determinants of computer acceptance, it has empirically emerged as the key theory in technology adoption literature across various research domains. In this regard, Chen and Li (2011) and Shroff et al. (2011) found strong empirical evidence for the model's prowess in enhancing understanding of information communications technology (ICT) usage and acceptance behaviours. Similarly, Alomary and Woollard (2015) established that the technology acceptance model has consistently emerged potent in accounting for end-user approval of new technology in various research domains. Moreover, the flexibility of the model to be extended and adapted to incorporate other variables factors makes it a robust technology adoption framework.

Tobbin and Kuwornu (2011) observed that literature on the adoption of mobile money technology falls between the two main financial technology-related research domains of mobile payments and mobile banking services. Accordingly, the current study argues that the determinants of adoption of mobile banking and mobile payments should be applicable to a mobile money adoption context as well. Suki (2010), Tobbin (2013), Alsamydai et al. (2014), Hanafizadeh et al. (2014) and Chitungo and Munongo (2013) are some empirical studies that substantiated the applicability of the technology acceptance model to internet banking, mobile banking, mobile money transfers and mobile payments. These studies reported that the constructs of perceived usefulness and perceived ease of use have a substantial positive impact on the adoption of mobile financial innovations, a finding that supports the validity of the technology acceptance model.

In Ghana, Tobbin (2010) used a cross-sectional survey to test the applicability of the technology acceptance model in the adoption of mobile money transfer services' domain. The study found that increased perceived usefulness intensifies consumers' mobile money adoption intention. Furthermore, Tobbin (2010) notes that perceived ease of use such as simplified registration processes, easy to follow payment instructions, use of the most basic cell phones and software, uninterrupted service availability, and a wide distribution of service agents all encourage mobile money adoption.

In another study which combined quantitative and qualitative methodologies, Tobbin (2013) examined the validity of the technology acceptance model in a mobile money context. The study also upheld the predictive strength of the model in influencing the consumer's behavioural intentions. Tobbin (2013) reported that perceived ease of use had the greatest impact on the behavioural intention to adopt mobile money services. The study did however highlight the point that perceived usefulness and ease of use alone fail to exhaustively explain consumer mobile money adoption behaviour.

Chitungo and Munongo (2013) employed a cross-sectional survey to examine the predictive strength of an extended technology acceptance model in the adoption of mobile money services by unbanked rural communities in Zimbabwe. They concluded that perceived usefulness and perceived ease of use had a significant positive effect on a user's attitude and the intention with regard to mobile money adoption. The study further established that once users had the requisite aptitude to transact on the mobile money platform, they developed a strong sense of ease which enhanced adoption. Chitungo and Munongo's (2013) study highlights the notion that the technology acceptance model is significantly improved to account for mobile money adoption through the incorporation of additional variables such as costs, perceived risk, social norms and demographic factors. Alsamydai et al. (2014) used a survey in Jordan to assess the usefulness of an extended technology acceptance model in determining consumers' use of mobile banking services. The study determined that: (1) perceived ease of use had the greatest impact on consumers' attitude, intention and subsequent adoption of mobile banking services, and, (2) perceived usefulness positively influenced attitude, intention and adoption of mobile banking technology. These findings validated the predictive strength of the model.

Munir and Idrus (2013) employed the constructs of perceived ease of use and perceived usefulness to investigate the adoption of mobile financial technology in Indonesia. The findings of their study corroborate the technology acceptance model - perceived ease of use and perceived usefulness had a strong positive effect on the adoption of mobile financial services. In addition, the study found that perceived usefulness had a much stronger influence on the acceptance behaviour than perceived ease of use. Likewise, Sayid, Echchabi and Aziz (2012) investigated the applicability of the technology acceptance model to mobile financial services adoption in Somalia. Their findings also support theory – they established that perceived usefulness was a substantial determinant of mobile financial services' adoption. In a study conducted in Ghana, Osei-Assibey (2014) extended the technology acceptance model to analyse mobile money transfer services' adoption. The study found that perceived usefulness and perceived ease of use were the strongest drivers of the mobile money transfer services' adoption decision.

Similarly, Masinge (2010) employed an extended the technology acceptance model in Gauteng, South Africa. The study concluded that customers at the bottom of the economic pyramid would take up mobile banking services if they perceived them to be useful and easy to use. Likewise, Maduku and Mpinganjira (2012) used the technology acceptance model to investigate mobile banking technology adoption by customers in Gauteng, South Africa. Their study reported that perceived ease of use and perceived usefulness positively influenced the adoption of mobile banking technology, a finding that was consistent with the technology acceptance model. Wentzel et al. (2013) also tested the applicability of the extended technology acceptance model to mobile banking adoption in South Africa. They concluded that attitude and perceived ease of use were the prime motivators for mobile money adoption. In a study undertaken in Tanzania, Lema (2017) investigated the determinants of mobile financial services' adoption by the unbanked population. The study provided mixed results; while it established that perceived usefulness had a significant impact on mobile financial services' adoption, perceived ease of use was however found to be insignificant. This outcome is therefore at odds with the theoretical underpinning of the technology acceptance model, which argues that both constructs are significant determinants of technology adoption.

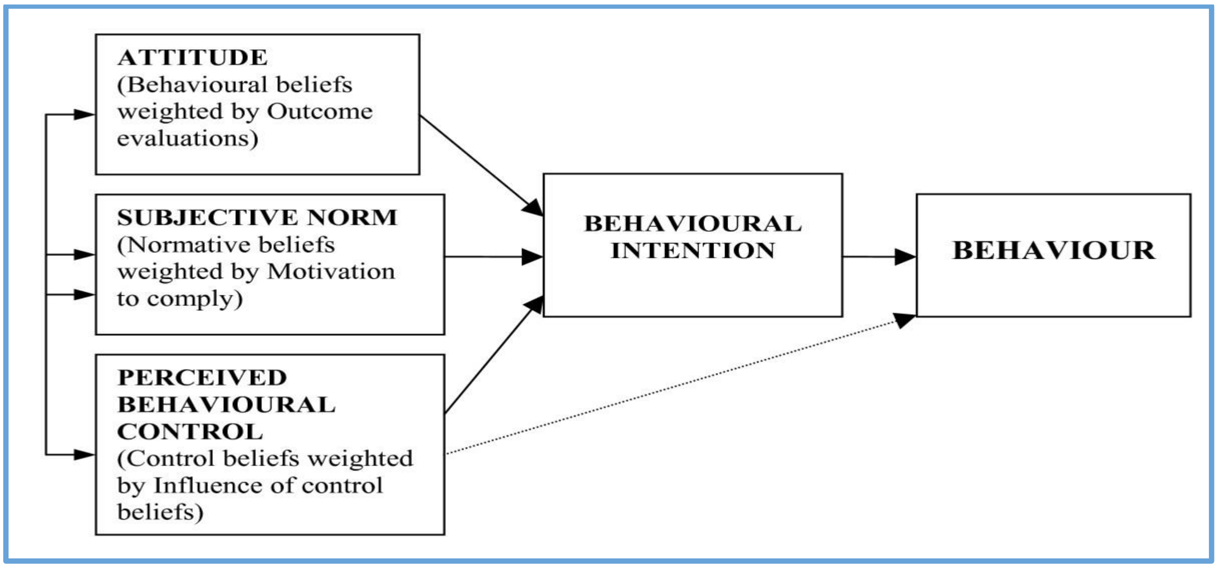
Despite the increased support for the validity of technology acceptance model especially in the information systems domain, it remains impossible to apply the constructs of perceived usefulness and ease of use solely when investigating technology adoption. Studies have criticised the technology acceptance model for being too modest, having a deterministic cause-effect approach, and overlooking vital moderating economic, demographic, perception, social norms and the cultural aspects of decision-making, which may alter user acceptance (Bagozzi, 2007; Venkatesh and Davis, 2000; Wu et al, 2011 Marumbwa and Mutsikiwa, 2013; Shaikh and Karjaluoto, 2015). In efforts to address these shortcomings, these studies suggest that additional variables were required to complement the constructs of perceived usefulness and perceived ease of use if the technology acceptant model is to meaningfully explain financial services'' adoption behaviour.

The technology acceptance model is discounted by Luarn and Lin (2005) for its assumption that there are no impediments which inhibit a user from accepting technology an individual so chooses. This assumption however does not hold for mobile money adoption behaviour because prior to an adoption decision, a potential user will consider other related factors including the cost of access, security and distance from the nearest mobile money service point. Furthermore, Pavlou and

Fygenson (2006) and Sommer (2011) criticised the technology acceptance model for diverting the attention of researchers away from the relevant subject matter. They reasoned that most studies based on the technology acceptance model over-emphasised the prominence of perceived usefulness of an innovation without giving requisite attention what makes it useful. Similarly, Thomas (2013) reported that the construct of perceived usefulness under the technology acceptance model was itself a subjective metric given that people have different perceptions of the utility of any technology. The current study notes that the technology acceptance model overlooked online social interactions as mediated by the internet, which take place between adopters and non-adopters of mobile money, and subsequently influence the latter's adoption behaviour.

The theory of planned behaviour (TPB) was proposed by Ajzen in 1991 as a modification of the theory of reasoned action. The diagrammatical representation of the theory of planned behaviour is shown in Figure 2.3 below.

Figure 2.3: Theory of Planned Behaviour



Source: Ajzen (1991)

Jokonya (2017) notes that the theory of planned behaviour sought to address the shortcomings of the theory of reasoned action by preventing behaviour prediction from being entirely under volitional control. The model introduces perceived behaviour control as another determinant of behavioural intention. Ajzen (1991) describes perceived behavioural control as an individual's perception of the ease or complexity of undertaking a certain behavior, which indicates a person's view of the required skills, resources, and opportunities in engaging in this behaviour. The theory of planned behaviour hypothesises that perceived behavioural control, subjective norms and attitude jointly determine behavioural intention, which in turn influences the ultimate conduct. In addition, perceived behavioural control directly impacts on the behaviour.

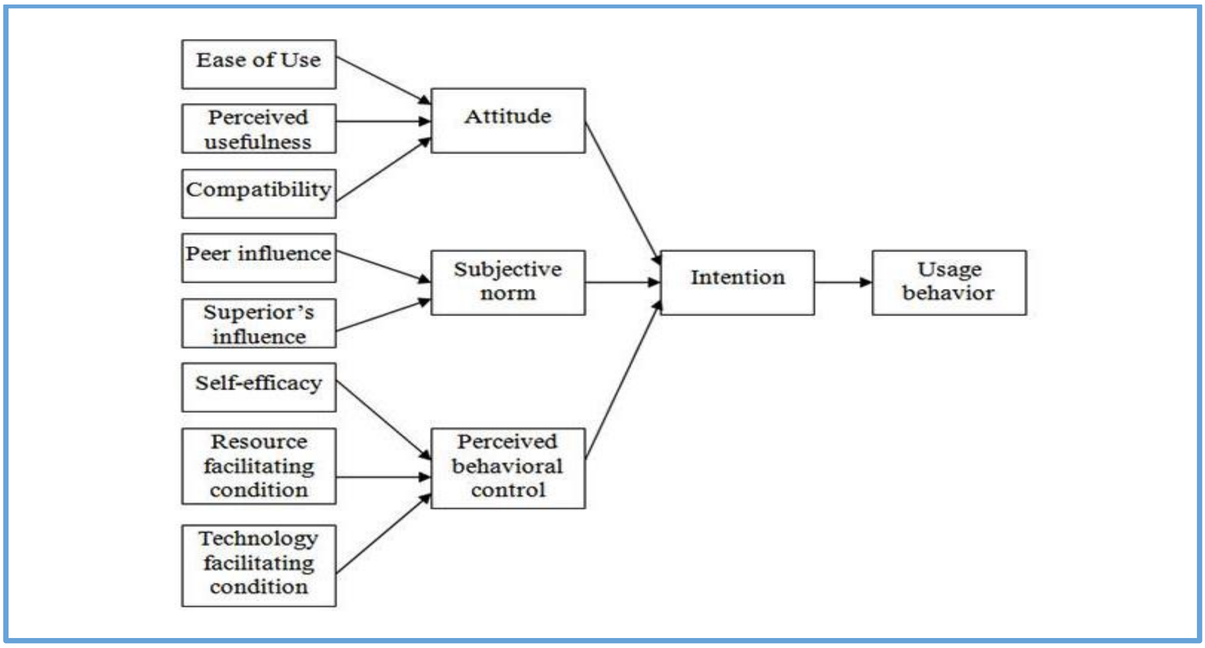
The applicability of the theory of planned behaviour has been extensively supported in empirical studies (Makena and Gekara 2014; Al-Fahim, 2013; Ndekwa et al., 2018; Omotayo and Adebayo, 2015). Makena and Gekara (2014) employed the theory of planned behaviour in Kenya to investigate the determinants of the behavioural intention to adopt mobile money services in institutions of higher learning. They found that subjective norms and perceived behavioural control significantly determined mobile money technology adoption, thus upholding the theory of planned behaviour's predictive power. Ndekwa et al. (2018) employed the theory of planned behaviour to examine university students' acceptance of mobile money services in Tanzania. Consistent with theory, the study reported that attitude, social pressure (vendors, classmates, sponsors, lecturers and friends) and facilitating conditions all had a significant impact on mobile money adoption.

Similarly, Al-Fahim (2013) analysed the drivers of internet banking technology use among postgraduate' students in Malaysia. The study concluded that attitude, subjective norms and perceived behavioural control positively influenced adoption, a finding which supported the theory of planned behaviour. Likewise, in India, Mishra (2014) employed the theory of planned behaviour to investigate users' acceptance behaviour towards mobile commerce. It was established that attitude and perceived behavioural control significantly affected adoption intention, while subjective norms were insignificant. Omotayo and Adebayo (2015) tested the theory of planned behaviour in internet banking adoption by postgraduate students in Nigeria. Consistent with the model, they concluded that attitude, subjective norms and perceived behavioural control strongly influenced adoption of internet banking technology. Likewise, Shih and Fang (2004) applied the theory of planned behaviour in Taiwan to determine the influence of effect of customer's attitude and subjective norms on internet banking technology adoption. The study reported that attitude significantly affected the adoption intention, while subjective norms are insignificant.

Despite supporting evidence from empirical literature, the theory of planned behaviour has been criticised by some scholars for being incomplete when applied to complex human behaviour. Ajzen (2002), Pavlou and Fygenson (2006), Jokonya (2010; 2015) and Thomas (2013) have all reported that this theory is inadequate as it excludes habits, emotions moderators and relationships between determinants predictors. While the theory of planned behaviour acknowledges the presence of subjective norms, the current study observed that these are limited to offline social interactions. Thus, the theory overlooked the effects of social media as mediated by the internet.

The decomposed theory of planned behaviour (DTPB) was developed by Taylor and Todd (1995) who linked the predictors of the theory of planned behaviour with the constructs of perceived usefulness and perceived ease of use in Davis' (1989) technology acceptance model. The decomposed theory of planned behaviour is depicted in Figure 2.4 below.

Figure 2.4: The Decomposed Theory of Planned Behaviour



Source: Taylor and Todd (1995)

The decomposed theory of planned behaviour was proposed to account for a significant amount of the variance in intention and actual behaviour. Taylor and Todd (1995) explain that attitude is influenced by three aspects: ease of use (complexity), perceived usefulness (relative advantage) and compatibility. The subjective norms construct is determined by peer influence and the superior's influence, while the perceived behavioural control belief is influenced by self-efficacy, resource and technology facilitating conditions. The theory further outlines that the constructs of attitude, subjective norms and perceived behavioural control jointly determine and individual's one's intention, which subsequently leads to the actual technology usage behaviour.

The predictive strength of the decomposed theory of planned behaviour has been extensively supported by existing literature. Pedersen (2005) employed an altered version of the theory to investigate the behaviour of early adopters of mobile financial technology. The study revealed that the modified model accounted for a large proportion of the mobile commerce adoption intention, a finding that validates the usefulness of the decomposed theory of planned behaviour. Similarly, in Jordan, Al-Majali and Mat (2011) employed the decomposed theory of planned behaviour to analyse adoption of internet banking technology. They found that the theory provided a comprehensive understanding of internet banking adoption. This finding substantiated the predictive strength of the model in a mobile financial services setting, and hence can be applied to mobile money technology adoption.

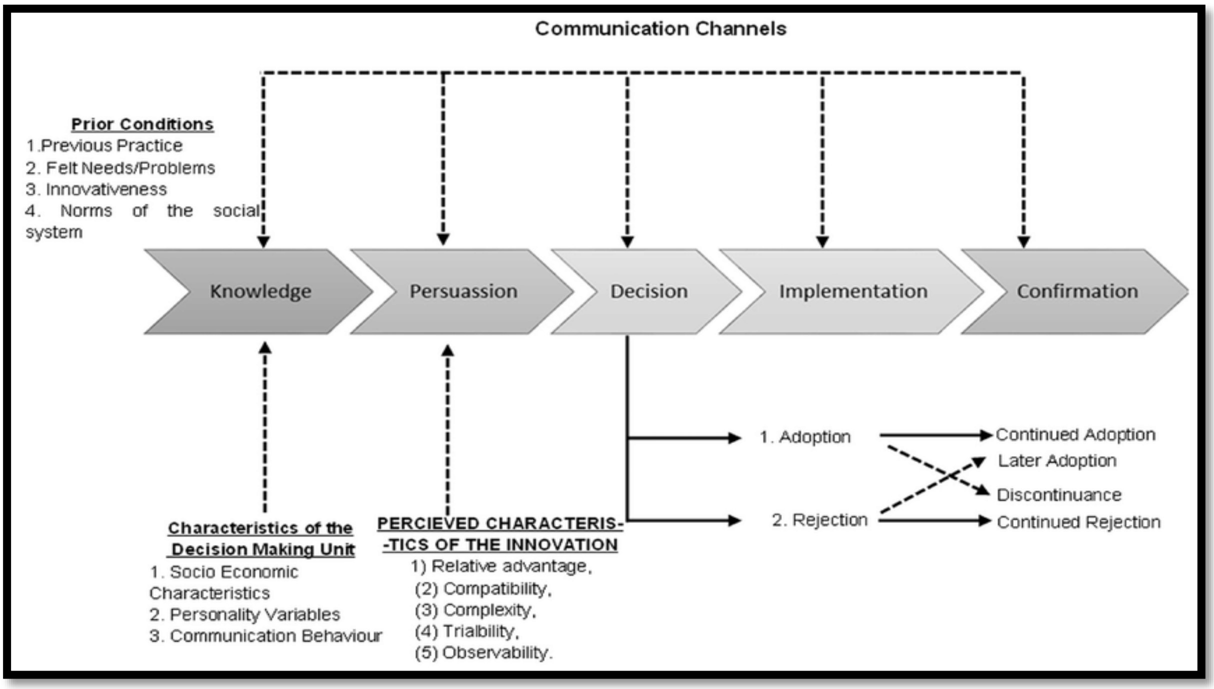
Kazemi et al. (2013) investigated the determinants of Iranian customers' intentions to adopt mobile banking, using an extended model of the decomposed theory of planned behaviour. They concluded that perceived usefulness, perceived ease of use, compatibility, and trust, subjective norms, self-efficacy and facilitating conditions had a positive impact on the adoption intention. However, Kazemi et al. (2013) established that perceived risk adversely affected mobile banking adoption intention. Omwansa (2012) applied the decomposed theory of planned behaviour in Kenya to analyse mobile banking adoption intentions, noting that the theory cannot be reliably employed in financial technology adoption studies owing to several constraints. First, the study found that the model was less parsimonious, fairly complex and had multiple mediating constructs that need to be collapsed. Second, the theory did not take moderating variables into account, thereby limiting its completeness. Third, the study established that the peer influence variable in the model, which in turn supposedly determines subjective norms was vague - its exact impact was therefore unexplained. Despite the inclusion by the model of subjective norms in the form of peer and superiors' influence, the current study notes that these however are offline and not social media effects, the subject matter of this research. Oversight of the social media in the decomposed theory of planned behaviour creates a gap in knowledge over the precise effect of social media in mobile money technology adoption decision-making behaviour.

The diffusion of innovation theory (DOI) was formulated by Rogers (1995; 2003) in order to explain how, why and at what rate new ideas and technology spread through societies and cultures. Rogers (1995) describes diffusion as a progression by which an innovation is communicated through certain channels across time among members of a social system. According to the diffusion of innovation theory, an innovation is an idea, practice or object that is perceived as novel by an individual or another unit of adoption. In addition, the communication process involves the innovation, an individual possessing understanding or experience of the innovation, an individual lacking such knowledge or experience, and a communication channel linking these two individuals. A communication channel may be mass media, which is usually the most effective means of informing an audience about an innovation. The diffusion of innovation theory proposes that interpersonal channels are often more effective in persuading an individual to adopt a new innovation. Rogers (2005:20-21) states that the time variable is present in the innovation-decision process to aid in specifying the innovativeness of an individual, and the relative speed of the adoption of an innovation.

The diffusion of innovation theory also proposes that the innovation adoption decision process involves five stages, namely: knowledge, persuasion, decision (adoption or rejection), implementation and confirmation. Rogers (2003) argues that these five stages of the innovation adoption decision process are facilitated by prior conditions, characteristics of the decision-making unit and the perceived characteristics of the innovation. There are five distinct attributes of an innovation that influence an individual's decision to adopt the innovation - relative advantage, compatibility, complexity, trialability and observability. Rogers (1995) explains that relative advantage is the degree to which an innovation is perceived as being superior to the idea it supersedes. Compatibility is described as the extent to which the innovation is perceived as consistent with the existing values, past experiences, and needs of the receivers. Complexity refers to the extent to which an innovation is believed to be relatively difficult to understand and use, and is negatively related to its rate of adoption. Trialability is the degree to which an innovation be tested on a limited basis, while observability is the degree to which the results of an innovation are visible to others.

Figure 2.5 below depicts the innovation diffusion process, indicating the interaction of the prior conditions, communication channels, distinct features of the decision-making unit, and the perceived characteristics.

Figure 2.5: The Innovation-Decision Process



Source: Rogers (2003:170)

The diffusion of innovation theory is upheld in empirical literature that focuses on financial services adoption. Osei-Assibey (2014) investigated the adoption of mobile money technology by small savings users and collectors in Ghana. In line with theory, the study established that trialability, observability, compatibility and the level of awareness by mobile money by users were all key determinants of mobile money adoption. Likewise, in Indonesia, Yunus (2012) examined the influence of the diffusion of innovation constructs (relative advantages, compatibility and trialability) on customers' mobile banking adoption intention. The study found that while relative advantages, compatibility and trialability had a significant positive impact on consumer attitudes, the compatibility variable was insignificant. These results largely support the diffusion of innovation theory in accounting for mobile financial technology adoption.

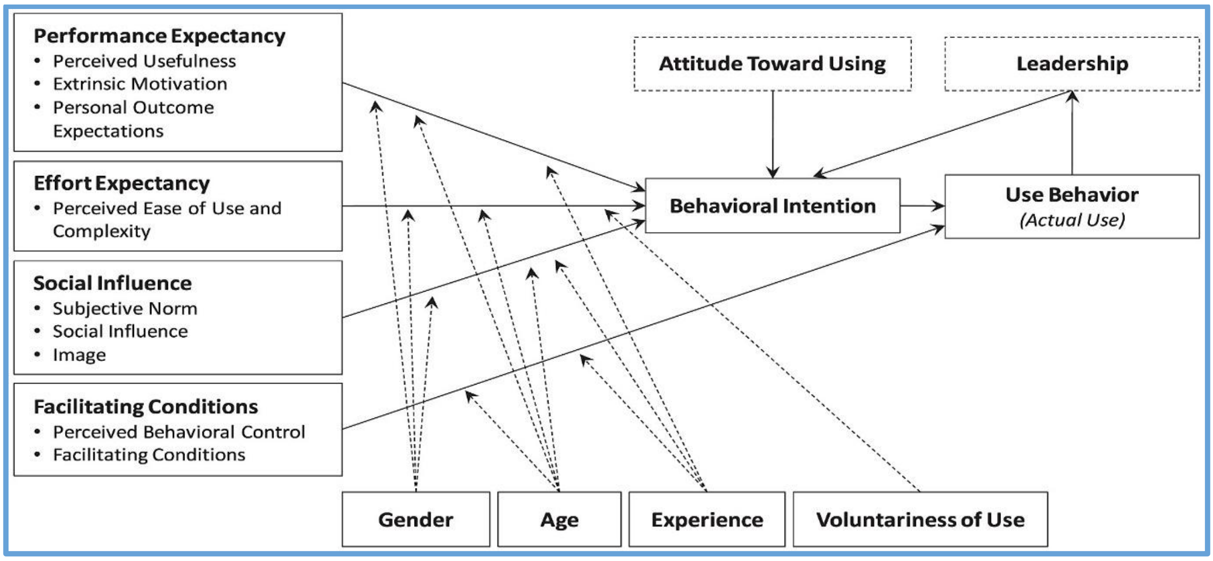
Chemingui and lallouna (2013) employed the diffusion of innovation theory in Tunisia to examine the inhibitors and motivators of the adoption of mobile financial services. They concluded that the constructs of compatibility, trialability and perceived enjoyment (relative advantages) had a positive effect on the intention to use mobile financial technology. Al-Jabri and Sohail (2012) also tested the applicability of the diffusion of innovation theory to determine what influenced the adoption of mobile banking services in Saudi Arabia. They established that relative advantage, compatibility and observability had a positively impact on adoption. However, contrary to the theoretical underpinnings, the study found that trialability and complexity constructs did not have influence mobile banking adoption.

Despite the applicability of the diffusion of innovation theory in technology adoption, Chile (2017) denounces it for being simplistic as it focuses solely on the innovation while overlooking complex economic factors (such as necessary infrastructure development and costs), societal networks, legal, cultural and information constraints that determine how the product is adopted by society. In addition, although Rogers (2003) incorporated social norms in predicting the adoption or rejection of technology, such norms are very general customs or expectations of a given community and are narrowly limited to an individual's close ties. The exclusion of social media as a determinant of mobile money technology usage in the diffusion of innovation theory potentially limits its predictive ability to offline communications - physical interactions, cell phone calls and texts. The current study addresses this gap by exploring the probable link between social media effects on mobile money adoption in developing countries.

Although the diffusion of innovation theory addresses some features of adoption such as immediate adoption, later or continuous adoption, rejection, discontinuance and for continued rejection, Omwansa (2012) discounted the theory as being more focused on the process of diffusion and less on the actual adoption. Ayodele (2012) pointed out that the theory's chief drawback was the fact that it is linear and source-dominated: it interprets the communication process from the view point of elite members of society who decide to diffuse the information or innovation. Empirically, however, the adoption of mobile money services is predominantly undertaken by those at the bottom of the pyramid and not the elite (Masinge, 2010; Chitungo and Munongo, 2013). In addition, Jokonya (2017) reported that while the diffusion of innovation theory was an advancement from an organisation's view, it was still deterministic in nature and more focused on the innovation, ignoring the social context of the information systems discipline. Omwansa (2012) does however observe that despite the model's lack of comprehensiveness in accounting for technology adoption behaviour, the diffusion of innovation theory has been a valuable basis for understanding the technology adoption decision-making process, particularly the persuasion characteristics and prior conditions.

The unified theory of acceptance and use of technology (UTAUT) was developed by Venkatesh et al. (2003) as an amalgamation of the components of other technology adoption theories, namely: the theory of reasoned action, the theory of planned behaviour, the decomposed theory of planned behaviour, the technology acceptance model, the diffusion of innovation theory, the social cognitive theory and the motivational model. According to the unified theory of acceptance and use of technology, the constructs of performance expectancy, effort expectancy and social influence directly determine the behavioural intention of technology acceptance, which in turn influences the actual use. The facilitating conditions, on the other hand, are a direct determinant of usage behaviour. The key moderators in the model are age, gender, experience and the voluntariness of use. The unified theory of acceptance and use of technology model is shown in Figure 2.6 below.

Figure 2.6: The Unified Theory of Acceptance and Use of Technology Model



Source: Venkatesh et al. (2003)

In line with Venkatesh et al. (2003), Abu-Shanab, Pearson and Setterstrom (2010) commended the unified theory of acceptance and use of technology as a refreshing view that represented a shift from the fragmented view of information technology adoption to a unified single theory. Omwansa (2012) tested the efficacy of the unified theory of acceptance and use of technology by applying it to mobile money adoption patterns at the bottom of the pyramid in Kenya. The results thereof were consistent with the theoretical underpinning - performance expectancy, social influence and perceived trust positively influenced mobile money adoption among the poor. Furthermore, the study revealed that despite appearing complex in terms of relationships, the unified theory of acceptance and use of technology is capable of explaining technology adoption as it is a union of several models with more comprehensive constructs than any other model. Moreover, Omwansa (2012) concluded that the model constructs were well laid out, making it easy to comprehend. Despite the model lacking some constructs such as innovativeness and trialability, Omwansa (2012) stressed that it nevertheless provided a good basis upon which mobile money adoption studies could build their research frameworks.

Yu (2012) employed the unified theory of acceptance and use of technology to examine drivers of mobile banking adoption in Taiwan. The study found that an individual's intention to adopt mobile banking services was significantly influenced by perceived credibility, perceived financial cost, performance expectancy and social influence. Furthermore, Yu (2012) established that mobile banking adoption behaviour was determined considerably by individual intention and facilitating conditions, an outcome which validated the unified theory of acceptance and use of technology's predictive strength from the perspective of mobile financial services' adoption.

Jaradat and Al Rabaa (2013) employed the unified theory of acceptance and use of technology in Jordan to analyse the determinants of consumers' adoption of mobile commerce services. The study reported that adoption of mobile commerce services could be predicted by users' behavioural intentions, which in turn were determined by social influence, performance expectancy, and effort expectancy. Similarly, Al-Tarawneh (2016) tested the validity of the theory to identify factors prompting customers' mobile banking services' adoption in Jordan. The study concluded that social influence, effort expectancy, and performance expectancy all drove the adoption of mobile banking services. However, the studies by Jaradat and Al Rabaa (2013) and Al-Tarawneh (2016) ignored the social media effects as facilitated by the internet as a moderating variable - instead they focused on general offline social influences.

Mugambe (2017) employed both meta-analysis and primary data to determine the extent to which the unified theory of acceptance and use of technology accounted for the adoption of mobile money services by customers of micro, small and medium enterprises in Uganda. The study found that there was a strong positive association between behavioural intention and the social influence, habit and facilitating conditions constructs. The results therefore supported the predictive potency of the theory in a mobile money context. Likewise, in Somalia, Ahmed (2017) confirmed the efficacy of the theory in a study that examined the drivers of mobile money transfer technology adoption. Ahmed (2017) concluded that trust, satisfaction, perceived usefulness and subjective norms and satisfaction all had a significant positive effect on the adoption of mobile money transfer technology.

The first shortcoming of the unified theory of acceptance and use of technology is its failure to include an exhaustive list of important moderating factors such as social media, education, personal innovativeness, perceived risk and cultural considerations. In addition, the subjective norms identified in the empirical findings were general, offline social interactions, and not social media. Bryman and Bell (2011) contend that the model is merely a replication of the theory of reasoned action and the theory of planned behaviour. They argue that the model has very limited use in the prediction of individual behavioural intention to adopt an innovation as it is predominantly based on organisational contexts. Alomary and Woollard (2015) also criticise the model for its oversight of the issue of voluntariness, given that a mobile money adoption decision is not a mandatory act. Al-Gahtani et al. (2007) reject the theory for overlooking the culture of the community in which it is being applied.

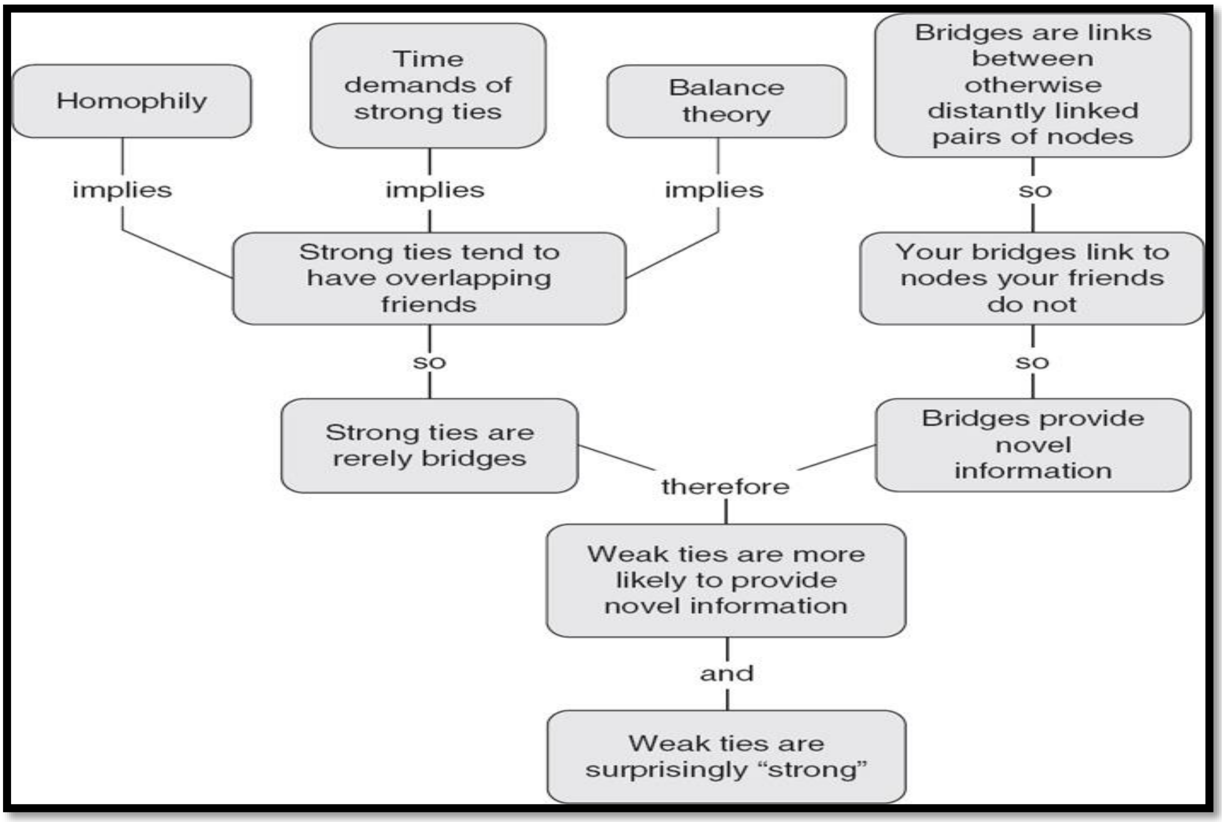
The current study selects the diffusion of innovation theory as the most appropriate model to account for mobile money technology adoption. The theory is preferred because it provides a better explanation of an individual’s technology adoption decision-than other adoption theories discussed here. While not exhaustive, the diffusion of innovation theory is cognisant of the various socio-economic, personality, communication, innovation characteristics and prior necessitating factors that influence mobile money adoption. Its prime strength is its inclusion of interpersonal relationships (social networks) as a communication channel through which innovations spread and are adopted or rejected by members of that social system. The diffusion of innovation theory is also employed to account for mobile money adoption in keeping with similar studies (Murendo et al., 2015; Lasserre, 2015). Therefore, the social network effects are regarded as considered to be closely related to the focus of the current study - social media.

2.3 THEORIES OF SOCIAL NETWORKING

Social networks refer to the individual members and the links between them through which information, money, goods and services flow (Maertens and Barret, 2013; Borgatti et al., 2009). Walther (2015) argues that social network analysis is premised an understanding of how links between individuals act as conduits for important and trivial resources such as information, capital, trust and advice. Christakis and Fowler (2013) and Langley et al. (2012) note that social network analysis is increasingly being applied across various research domains to better comprehend the dissemination of knowledge through relational ties where attitudes, beliefs and behaviours are transmitted between people. Empirical literature provides strong evidence that the adoption of novel products and or services diffuses along social networks (Fafchamps et al., 2017; Murendo et al., 2015a; 2015b; Beaman et al., 2014; Lasserre, 2015; Cai, de Janvry and Sadoulet, 2015). Social networks therefore help people to learn of product benefits from their friends and acquaintances and in turn to make informed adoption decisions. Three theories of social networking are discussed in this study, namely: the strength of weak ties, social learning and social contagion.

The strength of weak ties theory (SWT) was postulated by Granovetter (1973; 1983) and is grounded in social linkages. A diagrammatic summary of the strength of weak ties theory is shown in Figure 2.7 below.

Figure 2.7: Strength of Weak Ties Theory



Source: Granovetter (1973)

Granovetter (1973) classifies social connections into strong ties, consisting of family and friends, and weak ties, which are composed of acquaintances. In addition, the theory states that “the strength of a tie is a (probably linear) combination of the amount of time, the intensity, the intimacy (mutual confiding), and the reciprocal services which characterize the tie” (Granovetter, 1973:1361). Thus, the strength of weak ties theory proposes that new knowledge spreads through weak rather than strong ties because close relations are limited to the same social cliques. Subsequently, the information received within the close tie social networks overlaps substantially with what one already knows.

Acquaintances, on the other hand, are connected to other social links outside an individual’s circle of close friends and have dissimilar knowledge that overlaps less with what one already knows. Moving in different circles, acquaintances then connect an individual to a broader world, and may provide better sources when one needs information beyond what one’s own close tie social network group knows. Hence, weak ties are useful bridges to otherwise impenetrable social networks, and without weak ties, any benefits derived from strong ties would not spread beyond their clique.

Currently there is a paucity of empirical literature that specifically focuses on social networking and mobile money adoption. In order to address this shortcoming, the current study makes reference to closely related study matter - social networking and financial behaviour. Lusardi and Mitchell (2014) concluded that in the United States of America (USA), financial knowledge attained through social exchanges with others at work or in society (weak ties) had a strong positive effect on individuals’ financial behaviour. This finding is consistent with the strength of weak ties theory. Similarly, Acemoglu et al. (2011) and Gorodnichenko and Rolland (2011) established that highly cohesive group networks (strong ties) deterred the penetration of new technology in societies. Kinnan and Townsend (2012), consistent with Granovetter (1973), found that weak tie social networks effectively provided loans advances, and were thus useful for the smoothening of household consumption. Similarly, Di Falco and Bulte (2013) reported that strong tie networks dissuaded investment as a household risk mitigation strategy. In a study conducted in Western China, Zhang et al. (2012) also found that weak ties significantly improved the diversity of financial information acquired and the quality of the subsequent financial decision undertaken by a household.

However, studies where results were at odds with the strength of weak ties theory have revealed that a significant number of individuals who adopted mobile money services in developing countries did so following recommendations from family members (Intermedia, 2013; Kirui et al., 2012; Kikulwe, Fischer and Qaim, 2014). Likewise, in rural Mexico, Angelucci, De Giorgi and Rasul (2014) found that close (strong) ties allowed people to smooth their consumption and to realise returns on investments when compared to weak network ties. Also disputing the strength of weak ties theory, Walther (2015), Alatas et al. (2016), Giné, Karlan and Ngatia (2014) established that in many instances people relied on family and friends (close ties) for financial advice prior to making a financial decision.

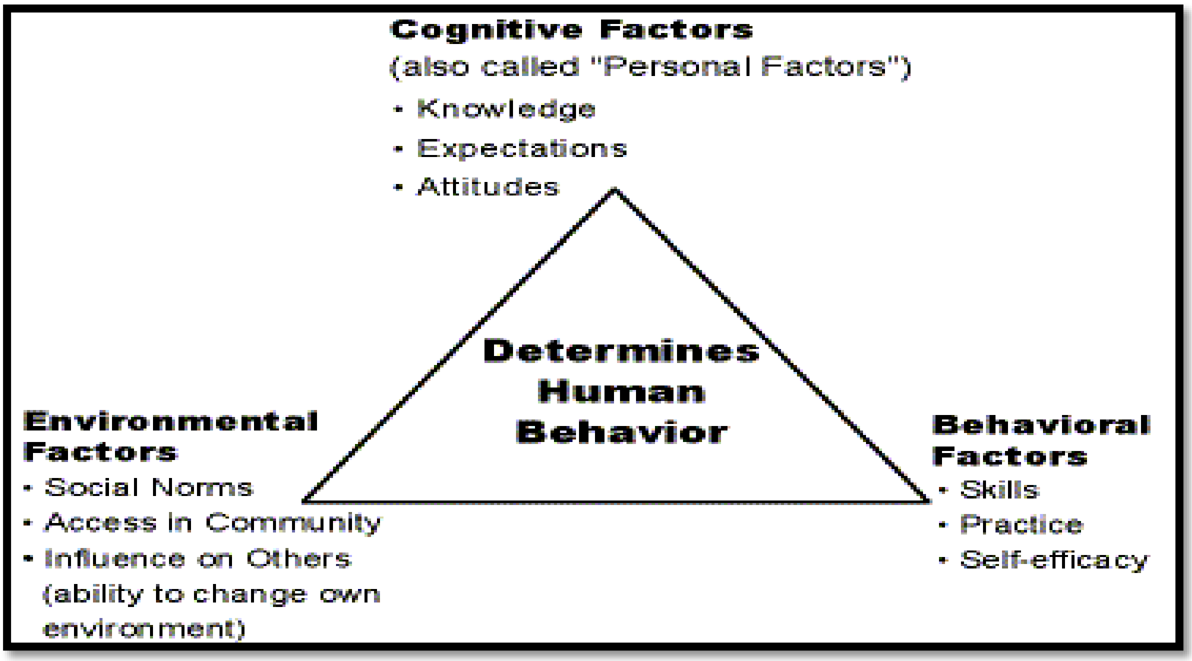
Interestingly, results from informal investigations in Uganda by Intermedia (2013) indicated that individuals adopted mobile money technology following recommendations from both close and weak social network ties (family members, friends and acquaintances). A study by Reich (2015) concluded that strong ties can have two-fold effects: (1) impeding innovation adoption by blocking the dissemination of information about a novelty among network members, or, (2) actively encouraging adoption among social network members. However, a study in rural Uganda by Murendo et al. (2015a; 2015b) found that a greater amount of weak ties within a household's social network contacts had no influence on the mobile money services' adoption behaviour.

Bandura's (1986) social learning theory (SLT) focuses on learning that occurs within a social setting. The theory proposes that one learns from: (1) one's own direct experience, or, (2) by observing and imitating the behaviour of others (a model). The more rudimentary form of learning, based on an individual's own direct experience, is mainly directed by the rewarding or punitive consequences that follow any given action. Through observation, the observer will imitate the model's behaviour if the model possesses characteristics the observer finds attractive. The observer will react to the manner in which the model is treated such as the rewards of convenience and security stemming from mobile money adoption.

When the model's behaviour is rewarded, the observer is more likely to mimic it, and when the model punished, the observer is dissuaded from imitating. It is essential to note that through observational learning but without an incentive to imitate the model (for example lack of mobile money adoption benefits), the observer may learn of a behaviour without any subsequent performance. Social learning through observation involves four distinct processes: (1) paying attention to a model's behaviour, (2) retention of information acquired, (3) possession of requisite skills for production of learnt behaviour, and (4) motivation to imitate the model's behaviour.

Bandura (1986) suggests that the environment also reinforces modelling or observational learning in several ways. Firstly, the observer is reinforced by the model, for example, an individual who adopts mobile money technology to fit in a particular social network has a strong likelihood of being accepted therein. Secondly, the observer is reinforced by another person when the observer might be imitating the actions of someone else. Thirdly, the imitated behaviour itself leads to reinforcing consequences where the learnt behaviour produces satisfying or reinforcing results (significantly reduced transaction costs by adopting mobile money technology). Therefore, modelling teaches new behaviour (awareness), influences the frequency of previously learnt behaviour (diffusion), may encourage previously forbidden behaviour (personal innovativeness) and increases the frequency of similar behaviour (mobile money adoption). The social learning theory is illustrated in Figure 2.8 below.

Figure 2.8: Social Learning Theory



Source: Bandura (1986)

The social learning theory has been empirically validated as accounting for product adoption. Fafchamps et al. (2017) established that when people discuss about financial innovations with fellow social network members, knowledge thereof is diffused through social learning. Consequently, some social network members who become informed of the novelty will proceed to adopt it. Accordingly, as people share knowledge about the hidden features of an innovation across their social networks, adoption spreads.

The social learning theory is also supported in mobile money technology adoption studies (Murendo et al., 2015a; 2015b; Fafchamps et al., 2017; Aker and Wilson, 2013). Murendo et al. (2015a; 2015b) found that non-adopters could make better informed mobile money adoption decisions when they interacted with and learned about the financial technology from early adopters. Likewise, Fafchamps (2017) and Aker and Wilson (2013) reported robust evidence for the effectiveness of social learning in spreading information about a new product (mobile money).

Lasserre (2015) investigated the three ways through which social networks affected the adoption of mobile money services in Uganda, that is, social learning, interactivity or network externalities and social contagion. The study confirmed the direct effects of social learning through peer adoption of mobile money technology. Furthermore, the study found that the support provided by social learning implied that an individual would increase his or her understanding of mobile money services through physical access to people whom he or she could observe and learn from. Therefore, a person with a large social network of mobile money adopters would be more likely to acquire the skills necessary to use mobile money. Nevertheless, like Murendo et al. (2015a; 2015b), Lasserre's (2015) study overlooked the use of online social networking platforms that are prevalent today, and instead focused on peer effects which are narrow and limited in reach with regard to information about an innovation.

Notwithstanding the validation of the social learning theory in empirical studies, the model has some shortcomings. The theory assumes that a model's behaviour to be copied has tangible benefits, yet financial behaviour and specifically mobile money adoption, is a latent act where only the benefits thereof can be communicated to the non-adopter. In addition, the theory requires that the model and non-adopter be within close proximity for such communication to occur. The social learning theory overlooks the possibility of social learning being mediated by social media, which has a wider and instantaneous reach of information across geographies. In addition, despite providing a good basis for understanding how behaviour takes place through a model, the social learning theory however lacks additional economic, demographic and environmental factors which influence an individual's adoption of mobile money technology.

The social contagion theory (SCT) was proposed by Burt (1987) having emerged from the social structure, and makes individuals in similar positions within the social network evaluate the merits and risks of adoption similarly. The theory is based on the concept of homophily, that is the extent to which two people who interact with each other are similar. Reciprocity and embeddedness are the two main attributes of the dyadic network relationship between the adopter and non-adopter of a technology in social contagion (Peng et al., 2014). Reciprocity refers to whether an adopter and non-adopter are mutual followers, which is meaningful only in directed networks. Embeddedness refers to the overlap between the adopter and the non-adopter's network members (Easley and Kleinberg, 2010).

Lasserre (2015) examined the adoption of mobile money technology in Uganda. In line with the social contagion theory, the study concluded that people with more social network members had an increased likelihood of adoption themselves as a result of social cohesion effects. Peruta (2018) established that adoption of mobile money services intensifies with the number of adopters in one's social clique. Peruta's (2018) study reported that increases in adopter individuals accelerate the diffusion of information on mobile money financial technology. Despite substantiating the social contagion theory, these two studies are nevertheless limited as they focus on traditional offline social networks effects while ignoring the use of social media.

The social contagion theory has two major weaknesses. Firstly, it is premised on the assumption of the homogeneity of individuals, which does not hold within a mobile money adoption context. The theory disregards the reality that individuals are heterogeneous (in terms of technology readiness, educational and economic backgrounds), which in turn affects the rate of adoption of mobile money (where some late adopters choose to observe the outcome of use by early adopters). Secondly, the idea that people will adopt an innovation when come into contact with others who have already adopted, as suggested by Langley et al. (2012), suggests the existence of physical (offline) contact social networks. These offline social networks are, however, a traditional form of interaction that is slow and too narrow in reach.

2.4 CHAPTER SUMMARY

A number of inferences have emerged from this chapter, and the prominent ones have been emphasized. The technology adoption and social networking theories applicable to this study were identified and discussed in detail. It was observed that existing literature on the mobile money technology adoption falls between the two main financial technology-related research domains of mobile payments and mobile banking. Accordingly, the current study argues that the determinants of the adoption of mobile banking and mobile payments should be applicable to mobile money as well. The technology adoption and social networking theories examined in the study attempt to account for mobile money adoption. The main gap identified in the empirical literature is the omission of social media use in the theories. While some models (the theory of reasoned action, the theory of planned behaviour, the decomposed theory of planned behaviour, the diffusion of innovation theory, the unified theory of acceptance and use of technology, the strength of weak ties theory, the social learning theory and the social contagion theory) acknowledge the role of social norms on financial technology adoption, the social interactions considered are not mediated through the internet as is social media. The present study attempts to augment this lack in empirical literature with the few available studies emerging from East Africa that focus on offline social networks (Fafchamps et al., 2017; Lasserre, 2015; Intermedia, 2013; Murendo et al., 2015a; 2015b; Kikulwe et al., 2014).

The offline social networks are, however, too narrow and capture only the traditional method of physical interactions (neighbourhood effects, phone calls and text messages). Therefore, offline social networks have a slow and limited reach because information about a financial technology is limited to an individual's immediate social circle. On the other hand, today social media is an essential means of communication that is mediated through the use of the internet. Social media facilitates a broader and more immediate reach of information across time and geographical location. The inclusion of social media in the study is a novel approach that permits an enriched understanding of how online social networking is likely to encourage the adoption of mobile money technology. The following chapter narrows the discussion by focusing on the relationship between social media and financial behaviour from both a theoretical and an empirical perspective.

CHAPTER 3

SOCIAL MEDIA AND FINANCIAL BEHAVIOUR

3.1 INTRODUCTION

The purpose of this chapter is threefold: (1) to discuss the theories of social media, (2) to analyse the impact of social media on financial behaviour from an empirical point of view, and (3) to examine additional factors influencing financial behaviour. The chapter is structured as follows: Section 3.2 discusses the relevant theoretical perspective of social media. Section 3.3 discusses the empirical literature on the social media-financial behaviour nexus. Section 3.4 examines other determinants of financial behaviour. Section 3.5 provides a contextualised model that links social media use to mobile money adoption, while section 3.6 concludes the chapter.

3.2 THEORIES OF SOCIAL MEDIA

Although there are many theoretical views of social media, only two are relevant to this study: Goffman's (1959) presentation of self and Bourdieu's (1977; 1992) social capital theory. These two theories have been used extensively in the domain of information systems research to analyse the use of social media. Goffman's (1959) presentation of self theory introduces the approach taken by an individual (agent) to objectively present him/herself to others. The presentation of self by the agent serves an objective - it expresses a view to others that is in accordance with the individual's self-interest. The presentation of self concept is premised on the outward appearance of action, which is first applied to the individual. Other people will then form an opinion about that particular individual through perceptual prudence.

According to Goffman (1959:4), the status of others is introduced by through the principle that an individual must present themselves in a manner in which others mimic the conduct. Qi et al. (2018) note that in terms of the presentation of self theory, social media is likened to a theatre production in which an individual conducts a performance. The individual will choose the features of him/herself that he/she wants to share with others on social media and present themselves in a convincing manner so as to influence their audience. Therefore, according to the presentation of self theory, a person will attempt to control the impression that others form of him or her. In other words, one has to know what others are likely to do and lead them towards a certain desired outcome.

Following Goffman (1959), empirical studies have reported that people use online social networks to present themselves as better than they actually are, to spread awareness of their own interests and to impress them on their social media network group members (Schwartz and Halegoua, 2015; Papacharissi, 2010; Edwards, 2015; Livingstone, 2008; Obee, 2012; Boyd, 2006). In addition, Cunningham (2013) substantiated the notion that people's behaviour appears to be customised for a particular audience. Qi (2018) has found that online micro-blogging platforms that permit posts to be seen publicly across a platform and be spread through likes and re-shares (such as the Twitter's re-tweet) are the most ideal effective communication conduits for influencing behaviour.

The social capital theory developed by Bourdieu (1977; 1992) asserts that all human behaviour is determined by social influence, and since the human mind is social, all individual rationality is dissolved into group effects. Bourdieu (1977) defines social capital as an accumulation of resources connected to the ownership of a durable network of connections of common acquaintance and recognition which is group membership. Empirical studies substantiate the social capital theory in social media use, especially through the use of microblogging platforms. Qi et al. (2018) have found that purposefully determining what to post, what information to share, and with whom to share it on a social media platform could amass immense social influence as the posts could become viral. Thus, online social networking platforms are an effective manner accumulating knowledge from other members (Evans, 2015; Carrigan, 2016).

A common feature - social influence, emerges from both Goffman's (1959) presentation of self and Bourdieu's (1977) social capital theory. This social influence therefore implies that it is social collectiveness rather than rationality that drives a desired behaviour on social media platforms. The ongoing sociability exchange of information among group members on these platforms becomes an effective, immediate and far-reaching diffusion conduit that alters individual behaviour through group or social network effects. Premised on these two theoretical underpinnings and on crucial empirical validations of these when applied to the use of social media, the current study therefore argues that social media influences financial behaviour, and more specifically mobile money adoption in the same way. In other words, online social networks are instrumental in impressing an individual’s mobile money adoption behaviour or interests on others within his or her networking group(s).

3.3 SOCIAL MEDIA AND FINANCIAL BEHAVIOUR: AN EMPIRICAL PERSPECTIVE

Research on the effects of social media on financial behaviour is still a new field, and as a result there currently exists limited literature. Xiao (2008) describes financial behaviour as any individual conduct that is connected to financial control. Household financial behaviour is the manner in which a domestic unit manages its financial resources through various means such as planning, budgeting and savings (Zakaria et al., 2012). Research shows that the use of social media provides external stimulus to recognize a need, thereby triggering general purchasing behaviour based on online reviews by peers and friends (Nyagucha, 2017; Kosavinta et al., 2017; McCormick and Livett, 2012; Gros, 2012; Khatib, 2016).

In this regard, Barhemmati and Ahmad (2015) examined how social network marketing influenced the ultimate consumer purchase behaviour among people who often used social networking websites in Malaysia. They established that respondents’ purchasing decisions were influenced by social media - people were more emotionally engaged after being involved in social network marketing activities, leading to positive purchasing behaviour from customers. Barhemmati and Ahmad’s (2015) study also revealed that people who spent time on social media platforms were more likely to be swayed by other network members’ ideas and feedback.

Madni (2014) examined the influence of social media on the buying behaviour of customers in Pakistan. The study found that social media had a substantial impact on consumption behaviour in Pakistan; prior to an online purchase, a substantial proportion of consumers referred to information from blogging forums, social media accounts, company websites, and peer reviews on social media platforms. Likewise, Hayta (2013) investigated the effect of social media on consumers’ purchasing behaviour in Turkey. The study established that social media have a strong positive influence on consumers’ purchasing behaviour. In a study conducted in Kosovo, Jashari and Rrustemi (2017) concluded that numerous consumers made unplanned purchases based on the information shared on social media platforms.

Empirical studies have validated the argument that the use of social media determines investment decisions (Heimer, 2016; Mudholkar and Uttarwar, 2015; Lugmayr et al. 2013; Kaustia and Knüpfer, 2012). These studies found that many high net worth investors were sceptical about the information provided by financial market firms and became increasingly reliant on the advice from their online social network contacts. In addition, the studies established that the use of social media helped prospective investors to learn more about an investment advisor through client reviews, thus providing essential insights into how a particular financial advisor worked and whether his/her their investment approach was appealing.

Similarly, Kavitha and Bhuvaneswari (2017) observed that online social networking platforms were used by investors to gather and share investment information because they provided timely, firm-specific industry updates which were essential in the investment decision process. Siganos et al. (2014) and Shanmugham and Ramya (2012) also concluded that investor sentiments shared on social media platforms were connected to the financial assets’ trading volume and stock price volatility. Furthermore, these studies reported that stock exchange investment was dependent on the attitudes investors obtained from online social networking interactions.

As noted above, empirical literature on how social media influences financial technology adoption behaviour is still in its infancy. The studies that are available focus on financial behaviour such as general purchasing, investment and crowdfunding decisions. For instance, Ammann and Schaub (2016) investigated the role of online social interaction in investment decisions by individuals, using unique data from a large European social trading platform covering the period from January 2013 to December 2014. The study sample contained more than 1000 investible strategies shared on the social online trading network, while the traders who managed the strategies posted about 20 000 comments on their profiles. Ammann and Schaub (2016) analysed the shared investment ideas, how traders communicated with followers about these ideas, the type of followers who traded based on the comments and followers' ultimate investment decisions. Ammann and Schaub's (2016) study concluded that online social trading networks enabled traders to implement trading strategies that followers could directly invest in. Secondly, the study established that there was a strong positive correlation between traders' online communication and the investment decisions of followers.

IBM Software (2012) analysed the impact of social media on high-value institutional investors' decisions in Asia, the USA and Canada. The study found that up to five million investors relied heavily on social media for the selection of fund managers and investment portfolios. However, IBM Software's (2012) study was limited in that it focused solely on developed economies, while the impact of social decision-making in developing countries remains as yet unknown. Moreover, the respondents in IBM Software's (2012) study were institutional investors, and as a result, failed to account for social media effects on financial behaviour of individuals. In contrast, the current study investigates the effect of social media on the use of mobile money technology by individuals in developing countries.

Likewise, an investigation of the role of social media in financial decisions on over 600 high-value investors in the USA and Canada was conducted by LinkedIn and Cogent Research and reported by Savio (2012). The study established that over 90% of high net worth investors patronised social media platforms such as LinkedIn, Facebook, Google+ and Twitter to conduct research prior to undertaking investment decisions. In addition, the study highlighted that LinkedIn attracted a significantly higher amount of affluent investors than other social networks. Also, Qin (2012) and Kaustia and Knüpfer (2012) concluded that investors who used social media were more likely to increase their stock market participation and risk tolerance levels compared to those who did not. They reported that investors put more trust in people they knew than financial advisors, and also weighed the information from online social networks stronger than professional advice before they undertook investment decisions.

Online social networking interactions have been observed to influence crowdfunding campaign successes. Crowdfunding refers to a form of early stage financing that raises money online by allowing business enterprises and people to interact directly with potential funders through the internet (Schwienbacher and Larralde, 2012). The growth of crowdfunding has been spurred by the scarcity of funding through traditional channels such as loans and venture capital (Beier and Wagner, 2015; Bains et al., 2014; Makina, 2017). The use of online social networks such as Facebook and Twitter has helped project initiators to promote their crowdfunding ventures, intensify reach, obtain direct feedback and build a rapport with potential benefactors. Therefore, increased numbers of online social networking platform connections by project creators are viewed as a success factor in crowdfunding campaigns because they are social capital for prospective projects (Giudici et al., 2013).

In Switzerland, Beier and Wagner (2015) analysed the determinants of crowdsourcing success employing a dataset of 740 projects from 100-days.net, an online crowdfunding platform. They established that a high frequency of project updates on social media platforms contributed significantly to the total campaign success. Similarly, Kerkhof (2016) examined the connection between online social interactions (proxied by the number of Facebook friends or likes) and the success of crowdfunding campaigns on European platforms such as Doorgaan, KissKissBankbank, Oneplanetcrowd and Voordekunst. The study found that a significant positive association between the social interactions and ultimate crowdfunding success.

Closely related to the social media-financial behaviour nexus are studies that focus on offline social networking and financial behaviour. West (2012) and Wachira and Kihiu (2012) found that despite being intellectually astute, individuals often behaved in an irrational financial manner, opting to blindly adopt the decisions of their trusted close family and friends with whom they were frequently in contact. Giné et al. (2014) reported that in many instances in Kenya, family and friends were often called upon for financial advice prior to making one’s financial decision. The strong reliance on social networks is upheld in both developed and developing countries, but is much more prevalent in the latter, owing to enormous informational asymmetries.

Credit is another financial product where some lenders have captured the power of social networking. Banerjee et al. (2013) partnered with a local microfinance institution in India to evaluate the effect of peers on microfinance services adoption. The study involved the collection of social network interactions data for 43 households over a period of six months prior to the availability of microfinance loan advances. Banerjee et al. (2013) established that a microfinance participant was an effective conduit for spreading information of the credit advances. They also reported that the household microfinance participation decision was highly influenced by information obtained from one’s closes peer network. Similarly, Wydick et al. (2011) found that church networks influenced microfinance borrowing by households in Guatemala.

Cai et al. (2015) investigated the effect of social networks on the adoption of weather insurance policies by village rice farmers in China. The study concluded that social network interactions could help people to undertake complex financial decisions as one would obtain simplified product information from family members and peers. Several field experiments have demonstrated the capacity of peer-based mechanisms to increase savings balances and loan repayment. Breza and Chandrasekhar (2015) confirmed that savings arrangements were contingent on the embedding of the savers and monitors in a social network. Their study employed a field experiment in 60 villages in South India where villagers were intent on saving. The savers were all given a bundle of services including assistance with account opening, savings goal elicitation and bi-weekly reminder visits by a surveyor. In addition, a randomly selected group among the savers received a monitor, a person who was updated about the savers’ progress every fortnight. Breza and Chandrasekhar’s (2015) study established that the randomly-chosen social network-monitored group reported substantial increases in savings (35% across all accounts) relative to the non-monitored group. Likewise, Kast, Meier and Pomeranz (2012) analysed the effect of social commitment on savings behaviour. Their experiment entailed working with microfinance borrowing groups, opening individual savings accounts for members, and randomly choosing some savers to receive monitoring by their microfinance groups. The study found that individuals in the peer monitoring treatment group saved almost twice as much as those in the control group.

Reviewed literature for the purpose of this study indicate that there are no other studies that have as yet specifically examined the influence of social media on mobile money technology adoption. In order to go some way towards filling this gap in the literature, this study discusses the empirical outcomes from studies on a similar subject matter - the influence of social networks on the adoption of mobile money services (Fafchamps et al., 2017; Murendo et al., 2015a; 2015b; Kikulwe et al., 2014; Munyegera and Matsumoto, 2014; Lasserre, 2015).

Fafchamps et al. (2017) investigated the impact of neighbourhood effects on the adoption of the ME2U airtime mobile money transfer service in Rwanda. They used social network data proxied by phone calls and airtime transfers from the start of 2005 until the end of 2008. The study found that increased use of ME2U by social neighbours translated into a higher probability of transferring airtime to another user. Also, Fafchamps et al. (2017) narrowed down the possible sources of these network effects by distinguishing between network externalities and social learning. In the case of social learning, the authors sought to distinguish between learning about the existence of the new product and learning about its quality or usefulness. Their findings provided robust evidence of social network influence on adoption from peer discussions on the reliability or usefulness of the mobile money transfer service. Despite providing insight into mobile money adoption, Fafchamps et al.'s (2017) study does, however, focus on social neighbourhood interactions which are offline in nature, and whose reach of information is limited to one's immediate social clique. Fafchamps et al. (2017) overlooked the impact of social media, a present-day communication channel, and additional demographic and contextual determinants of mobile money adoption.

In rural Uganda, Murendo et al. (2015a; 2015b) used a cross-sectional survey to examine the effect of social networks on the adoption of mobile money by households. The social networks' effects were proxied by the following: (1) the number of social exchange members, (2) weak ties or the structure of the social network, and (3) the social network education status. Murendo et al. (2015a; 2015b) concluded that the size of exchange adopters had a significant positive impact on household mobile money adoption. Furthermore, the studies established that the addition of one exchange adopter to a household social network substantially improved the likelihood of money adoption. Lasserre (2015) used a cross-sectional survey in urban Uganda to analyse the role of peer effects in the adoption mobile money services. The study found that peers had a significant positive influence on an individual's decision to use money technology. After disaggregating peer adoption by the type of social network, Lasserre (2015) reported that family and friends (close ties) explained the greatest proportion of peer influence on mobile money adoption. Similar to Murendo et al. (2015a; 2015b), Lasserre's (2015) study did not consider online social networking effects - the peer influence investigated in their study has a narrow reach of information on mobile money technology and adoption.

Kikulwe et al. (2014) employed panel survey data in rural Kenya to investigate household mobile money adoption. The study concluded that cell phone ownership improved the likelihood of household mobile money adoption due to increased information access. Kikulwe et al.'s (2014) study however did not specifically address social network effects, and consequently, these were only inferred from a household's mobile phone ownership. The same mobile phone ownership proxy however, does not distinguish social media interaction from calls and texts messages.

Table 3.1 below summarises the research findings from the studies discussed above that are closely related to social media-mobile money adoption nexus, the focus of the current study.

Table 3.1: Summary of Closely Related Studies.

Empirical researcher	Country	Variables Used	Impact on Mobile Money Adoption (Sign)
Fafchamps et al. (2017)	Rwanda	Social network effects	+
Murendo et al.(2015a; 2015b):	Uganda	1. Social networks proxied by: (i) Size of exchange adopters; (ii) Weak ties; (iii) Network education status. 2. Mobile phone ownership. 3. Gender of household head. 4. Off-farm income. 5. Ethnicity. 6. Religion	+ + No effect. No effect. + + + + +
Lasserre (2015):	Uganda	1. Peer adoption. 2. Education. 3. English literacy. 4. Perceived ease of use. 5. Perceived usefulness. 6. Income. 7. Close ties. 8. Weak ties. 9. Mobile phone skills.	+ + + + + No effect. + No effect. +
Kikulwe et al. (2014):	Kenya	1. Age. 2. Gender. 3. Education of household head. 4. Household size. 5. Wealth. 6. Distance to nearest banana market. 7. Distance to nearest road infrastructure.	No effect. No effect. + + + No effect. No effect.

Source: Author's compilation.

3.4 OTHER FACTORS INFLUENCING FINANCIAL BEHAVIOUR: AN EMPIRICAL VIEW

This section examines additional determinants of financial behaviour as provided in the empirical literature, some of which are used as control variables in the study. These variables include cost, household size, marital status, gender, religion, age, education, employment status, household location, income, trust, perceived risk, financial literacy, regulation, agent distribution network.

Cost refers to the extent to which a person believes that using a financial service would involve expending money (Chitungo and Munongo, 2013). The expenditures involved in mobile money transactions include the government tax levied per transaction, charges levied by the service provider and the amount paid to purchase the mobile device. Cudjoe et al. (2015), Dass and Pal (2011) and Narteh et al. (2017) argued that cost had a negative impact on the adoption of mobile financial services. Likewise, in South Africa, Masinge (2010) reported that low income individuals had low purchasing power and were price sensitive. Tobbin and Kuwornu (2011) and Ramdhony and Munien (2013) established that if consumers perceived that the cost of mobile money was acceptable they would adopt it more easily. On the other hand, Koening-Lewis et al. (2010) and Petrova and Yu (2010) could find no significant connection between service cost charges and behavioural intention to adopt mobile financial technology.

Household size can also influence financial behaviour in various ways. Baker and Ricciardi (2014) suggested that a large household inhibited asset growth and this observation continued over a household's lifetime. However, in studies conducted in East Africa, Murendo et al. (2015a; 2015b), Lasserre (2015) and Kikulwe et al. (2014) established that larger mobile money adopter households were more likely to influence their non-adopter members when compared to smaller households as a result of increased information. The present study assumes that increased household size leads to a higher probability of mobile money adoption.

Marital status has been found to impact on financial behaviour. Chattopadhyay and Dasgupta (2015), Arano, Parker and Terry (2010) found that married investors in

India were more risk averse than their unmarried counterparts. This outcome was premised on the understanding that single individuals had less to lose by accepting greater risk, whereas the married were often responsible for themselves as well as their dependents. In contrast, Christiansen, Joensen and Rangvid et al. (2015) established that in Denmark, marriage increased the likelihood of financial market participation, while Dayioglu and Gumus (2015) reported that in Turkey, marital status had no effect on investment decisions. The present study assumes that married people are more likely to adopt mobile money technology because of the need to remit money to dependent family members.

Gender is an additional determinant of financial behaviour. Badinenko, Barasinska, and Schafer (2011) and Kara, Mishra and Dash (2010) found that males undertook more financial services' adoption decisions than women. In support of this, some empirical studies have established that women are less likely to adopt mobile money technology than men (Van Hove and Dubus, 2019; Demirgüç-Kunt et al., 2018; Biscaye et al., 2017; FinMark Trust, 2016). Other investigations into mobile money adoption however, have revealed that there is no significant difference between males and females (Khan, Akter and Akter, 2017; Ramdhony and Munien, 2013). The current study assumes that men are more likely to adopt mobile money services than women.

Religion can affect financial decisions in various ways. In a study conducted in Poland, Czerwonka (2014) found that faith and religiosity played an important role in investors' willingness to engage in socially responsible investment. The religious segments of the population were found to be more open to the idea of socially responsible investment than agnostic investors. The finding is consistent with Peifer (2011) and Hess (2012) who observed that individual investors relied on their religious morality to decide between investment alternatives. The influence of religion on mobile money adoption in developing economies however still remains to be established (Murendo et al., 2015a; 2015b).

Age is identified as another determinant of financial behaviour. Some studies (Maheshwari and Mittal, 2017; Onsomu, 2015; Gamble et al., 2015; Lachs and Han, 2015; Korniotis and Kumar, 2011; Jain and Mandot, Agarwal et al., 2009) have reported a deterioration in financial decision-making with advances in age. Likewise, Samanez-Larkin et al. (2010) noted that in risky asset selection, older people made more mistakes than young investors. Choi et al. (2014) observed a considerable negative relationship between age and the consistency of choices with economic rationality. In contrast to the above studies, Edelman (2015) concluded that the advancement in age did not have an adverse impact on investment decisions. The current study assumes that young adults are more likely to adopt mobile money services than the elderly.

Literature also identifies the influence of educational attainment on financial behaviour. Chattopadhyay and Dasgupta (2015), Jain and Mandot (2012) and Gilliam and Chatterjee (2011) argued that higher educational attainment encouraged people to take more financial risks than those with lower levels of education owing to increased information. In contrast, Hallahan et al. (2003) found that educational attainment was an insignificant determinant of an individual’s risk tolerance behaviour. The current study assumes that highly educated individuals are more likely to adopt mobile money services than their less educated or uneducated counterparts.

An individual’s employment status has been observed to lead to different financial behaviour outcomes. Studies indicate that employed individuals display higher financial risk tolerance than the unemployed since they are more likely to be capacitated to participate in financial activities, and to take on more risks (Chattopadhyay and Dasgupta, 2015; Jain and Mandot, 2012). Interestingly, on the other hand with respect to mobile money innovation, FinMark Trust (2016) established that the unemployed are more likely to adopt mobile money than the employed. This shows the potential of mobile money envelop the unemployed into the formal financial system

Geographical location also influences financial behaviour. Jain and Mandot (2012) found a positive relationship between cities and investors’ level of risk tolerance. Differences in adoption rates of mobile financial services between urban and rural populations were also reported by GSMA (2014), Lwanga and Adong (2016), Intermedia (2013) and Marumbwa and Mutsikiwa (2013). Likewise, the current study expects mobile money adoption in urban areas to be higher than in rural areas.

Empirical studies are divided over the effect of income on financial behaviour. Some studies (Jain and Mandot, 2012; Rooij, Lusardi and Alessie, 2011) concluded that an individual's risk tolerance increased with rising income levels. Such results suggested that low income investors had lower risk tolerance, implying that they were risk averse because they had little flexibility in their regular budgets. In support of this, Zakaria et al. (2012) established a positive correlation between financial behaviour and income. Likewise, Van Hove and Dubus (2019) reported that from Kenya, the poor were predominantly less likely to adopt mobile money technology. However, mobile money is a low-cost solution targeting the poorest, with only a low purchasing power required. Accordingly, the current study assumes a positive association between income and mobile money adoption.

Trust is an additional factor observed to affect one's financial behaviour. Maduku and Mpinganjira (2012) perceived trust as the customer's feeling of security, confidence, and the willingness to depend on a system, product or service in the belief that it will not disappoint them. In Spain, Letamendia and Silva (2017) found that lack of trust in formal financial institutions as a result of financial scandals, corruption, economic crises, political instability and elevated perceived risk of financial intermediaries adversely affected investment and savings. Cudjoe et al. (2015), Alsamydai et al. (2014) and Masinge (2010) noted that high levels of trust in a service provider led to intention on the part of the user to adopt mobile banking technology. Similarly, in India, Dass and Pal (2011) found a significant positive correlation between trust and adoption of mobile financial services among the rural unbanked.

The perceived risk associated with the use of a financial product and or service determines its use. Perceived risk presents uncertainty, a potential loss or security compromise, which may result in a loss (Chitungo and Munongo, 2013). By nature, mobile money technology is a service, and its perceived risk is typically greater than that of a tangible product. The perceived risk associated with a mobile money service could be financial, social, performance or psychological (Kim, Jang, and Yang, 2017; Paluch and Wünderlich, 2016). The adoption of mobile financial technology gives rise to concerns that there may be financial losses, password insecurity, network errors, hacking and loss of personal information. Studies have found that perceived risk represents a substantial barrier to mobile banking and mobile money services' adoption (Ramdhony and Munien, 2013; Shin, 2010; Tobbin and Kuwornu, 2011).

Financial literacy is an additional determinant of the decision to adopt financial services or products. Financial literacy involves learning about choosing between a multiplicity of options, setting personal financial goals and reflecting on the value of money (Criddle, 2006:4). Empirical literature established that financial literacy positively influenced individuals to undertake more financially responsible behaviour such as higher savings, wealth accumulation, retirement planning, active debt management, market discipline and financial inclusion (Letamendia and Silva, 2017; Refera et al., 2015). Despite increased financial knowledge, however, Lusardi and Mitchell (2011) noted that people still opted for sub-optimal retirement funding plans. Interestingly, Xu and Zia (2012), Cole et al. (2014), and Alex and Amos (2014) concluded that there was no association between financial literacy and resultant financial behaviour.

A country's regulatory framework also determines the adoption of mobile money adoption services (Mahmoud, 2019). A flexible and enabling regulatory environment helps to improve the accessibility of the financial innovation. Maina (2018) reported that easing the know-your-customer requirements to facilitate new customer registrations encourages use of mobile money services. Furthermore, a stance by a country's mobile money regulator to facilitate an effective working rapport with all mobile money regulators is therefore an important driver of all mobile money services.

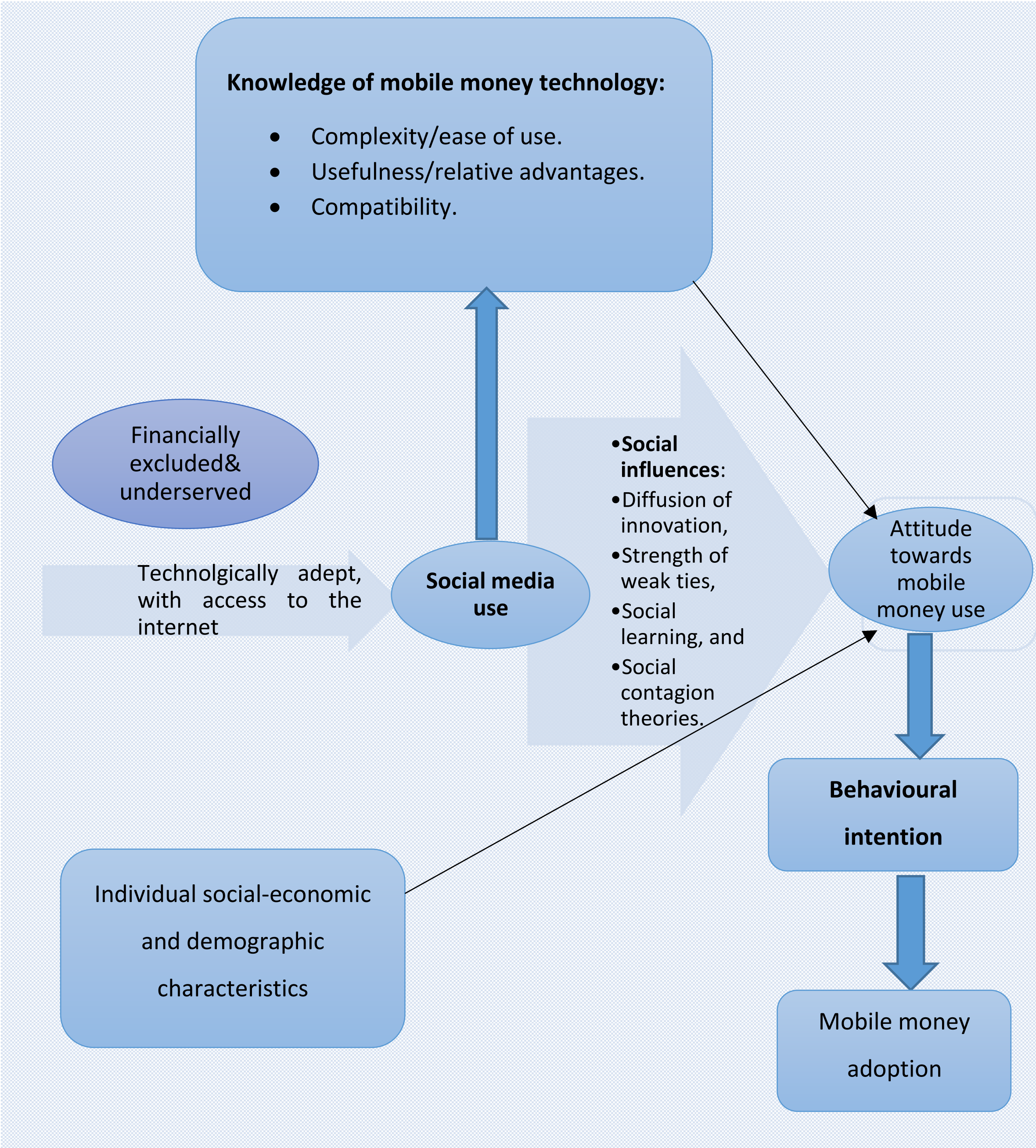
The adoption of mobile money services is also determined by the agent distribution network. Service providers encounter difficulties in attracting and retaining mobile money service adopters due to inefficiency of agents (Mahmoud (2019). Ideally, the mobile money services' agent outlets must be located within close proximity to the customers they will serve, and efficiently provide services such as account registration, cash-in or cash-out and educating the customers. In addition to the mobile money operator's outlets availability, Mahmoud (2019) also noted that scaling up the quality of services rendered by mobile money services' agents encourages adoption of the services.

3.5 HYPOTHESIZED LINK BETWEEN MOBILE MONEY AND SOCIAL MEDIA

An integrated conceptual model comprising: (1) the diffusion of innovation theory, social media effects, and (2) demographic, socio-economic and other contextual factors as indicated by the existing literature was chosen for use in the current study.

The study hypothesises that mobile money adoption by the financially excluded and under-served individuals is influenced by use of social media through the moderating effects of attitude and the behavioural intention. The use of social media allows the spread of knowledge about mobile money technology, raises awareness among non-adopters, and influences their attitude towards the financial innovation. In addition, the use of social media is determined by an individual's technology adeptness, access to the internet, socio-economic and demographic characteristics. Behavioural intention on the other hand is affected by attitude towards mobile money adoption. Attitude towards the adoption of mobile money technology is itself subjected to: (1) the individual's socio-economic and demographic characteristics, (2) the extent of the individual's knowledge of mobile money technology obtained from one's online social network contacts. A person's knowledge of mobile money technology entails the understanding of perceived ease of use/complexity, perceived usefulness/relative advantages, compatibility, and social influences (social learning experiences, strong and weak ties). A diagrammatical illustration of the research contextual framework is shown in Figure 3.1 below.

Figure 3. 1: Research Conceptual Framework



Source: Author

3.6 CHAPTER SUMMARY

A number of conclusions have emerged from this chapter and the most dominant ones have been highlighted. Studies on how social media influences financial behaviour are still novel, and consequently, empirical literature on how social media influence financial technology adoption behaviour is also in its infancy. The majority of studies focused on broad financial behaviour such as general consumer purchasing decisions, investing and crowdfunding (Ammann and Schaub, 2016; Khatib, 2016; Kuchciak, 2013; Hayta, 2013; Barhemmati and Ahmad, 2015).

It also became clear that there were no empirical studies that focused specifically focus on social media and mobile money adoption. In response, reference was made to studies on social media and broad financial behaviour, as well as social networking and mobile money adoption. Studies established that: 1) social media had a significant effect on financial behaviour, and 2) social networks positively influenced mobile money adoption through the diffusion of information about the innovation. The chapter also discussed demographic and other contextual factors influencing financial behaviour, and inferences were made with regard to mobile money adoption. Costs, gender, age, geographical location and perceived risk were found to impede adoption, while household size, education, financial literacy, religion, income, trust and employment suggested an increased likelihood of adoption of financial services. The following chapter describes the methodology used to determine the influence of social media on mobile money adoption.

CHAPTER 4

RESEARCH METHODOLOGY

4.1 INTRODUCTION

The preceding two chapters investigated the theories of technology adoption, social networking, social media and the social media-financial behaviour nexus. This chapter discusses the methodology followed in determining the influence of social media use on mobile money adoption in South Africa and Zimbabwe, through the use of regression techniques applicable to the study. An evaluation of the comparative merits and demerits of identified regression models was undertaken with a view to selecting an appropriate methodology for the current study. The chapter presents the research design for this study by describing the statistical techniques employed to test the objectives set out in the introductory chapter. Overall, the research design, study variables, methodological issues, main estimation model and robustness checks selected for the study were influenced by the type of data and methodologies used in prior, closely-related studies that were relevant to the current research.

The remainder of the chapter is divided into seven sections. Section 4.2 outlines the methodological issues and techniques employed in prior related studies. Section 4.3 discusses data type, sources and collection methods. Section 4.4 discusses the main variables employed in the current study, their respective proxies and sources of extraction. Section 4.5 explains the main estimation model used in the study with the relevant model fit statistics. Section 4.6 provides an additional model employed for robustness checks in the present study, while section 4.7 focuses on the limitations encountered in the use of the chosen model and data. Section 4.8 concludes the chapter.

4.2 METHODOLOGICAL ISSUES AND TECHNIQUES USED IN RELATED STUDIES

The most common regression estimation technique is the ordinary least squares linear regression, also known as multiple or conventional regression analysis. Muchabaiwa (2013) notes that linear regression can be employed for data analysis only if the dependent variable is continuous, independent and identically distributed. Consequently, linear regression is rendered inappropriate in cases where the dependent variable is categorical or discrete (Verbeek, 2014; Muchabaiwa, 2013). Al-Ghamdi (2001) notes that in a scenario where the dependent variable has a binary or dichotomous outcome, the ordinary least squares estimation becomes biased and inefficient because of the non-linearity of the categorical dependent variable.

The logistic and probit regression models are alternative methods for estimating binary dependent regression models that force the predicted values to fall between 0 and 1, thereby imposing some curvature on the regression model instead of a straight line produced by linear modelling (Fenella, 2016). The binary probit and logistic models are classes of binary choice or univariate dichotomous models that are then employed to model the choice between two discrete alternatives (Verbeek, 2004:191). These models are premised on the notion that the observable dependent variable takes on the value of 1 if an event occurs, or 0 if not. The categorical dependent variable in the binary logistic and probit model estimations uses the maximum likelihood estimation method, unlike the moment based method used for the ordinary least squares technique (Greene, 2008; Park, 2009; Mudiwa, 2011; Kind, 2014).

The binary logistic model, also known as logit regression, assumes a standard logistic distribution function and has its origins in medical research, although these days it is employed across all disciplines (Mudiwa, 2011). O’Connell (2006) in Nederpel (2012: 45) notes that “logistic analyses for binary outcomes attempt to model the odds of an event's occurrence and to estimate the effects of independent variables on these odds”. The binary logistic regression, like any other model, seeks to find the most appropriate, most economical and yet practical model to evaluate the link between a dependent variable and at least one independent variable. The distinct features of the binary logistic model have led to its frequent use in regression analysis (Wittink, 2011; Greene, 2012; Verbeek, 2004; Long, 2007). Firstly, the logistic model error terms are presumed to follow the standard logistic distribution, and as a result the binary logistic regression technique offers more robustness. Secondly, the method does not assume a linear relationship between independent variables and the dependent variable, and for this reason can handle non-linear effects. Thirdly, one can add explicit interaction and power terms to the logistic model. Fourthly, the binary logistic model is flexible since it assumes that there is no homogeneity of variance, and that the error terms are not normally distributed. Finally, the method does not require the independent variables to be unbounded.

A binary probit model, on the other hand, is defined by Wilson and Lorenz (2015:18) as a type of regression model for binary data that depends on the cumulative distribution function of normal distribution. This model thus assumes a standard normal distribution function of the error terms (Mudiwa, 2011). The first assumption on normality for the binary probit model is a very convenient supposition because it improves its analytical prowess; it may also be a disadvantage however, as a normal distribution is then required for all unobserved components. Secondly, the integral for choice probabilities has an open form for the probit model, but this feature makes estimation computationally intensive (Wittink, 2011). Greene (2010:756) argues that the probit model's major merit is its efficacy in providing grounding "for theoretical econometricians such as those who have developed methods of bias reduction for the fixed effects estimator in dynamic nonlinear models". Greene (2010) and Murendo et al. (2015b) have, however, observed that similar to other modelling settings, endogeneity of some independent factors poses a considerable complication in the estimation and use of the probit model.

The essential dissimilarity between the binary logistic and probit models observed from literature is in the distribution of error terms; the binary logistic model error terms are presumed to take the standard logistic distribution, while the probit model follows a normal distribution. Also, the probability density function of the probit regression model has a higher peak and thinner tails in comparison to the standard logistic probability distribution. In addition, the cumulative density function of the probit regression model is steeper in the middle than the cumulative density function of the standard logistic distribution and quickly approaches zero on the left and one on the right (Patnaik and Sharma, 2013; Greene, 2012; Wittink, 2011; Verbeek, 2004; Long, 2007; Maddala, 1983).

Fox (2010) also compared the binary logistic and probit models and notes several differences. First, the equation of the logistic cumulative density function was reported to be very simple while the normal cumulative density function for the probit model involved an unevaluated integral. Secondly, Fox (2010) established that the ease of interpretation of results obtained using the logistic model was the direct result of interpretable log-odds, compared to probit inverse transformation which does not have a direct interpretation. Thirdly, Wilson and Lorenz (2015) have found that the capability of the binary logistic model to model the odds made it very popular among researchers since probability is dependent on odds, and the odds can always be determined across all types of data. Fourthly, studies note that the binary logistic and probit models were scaled differently (Verbeek, 2004; Park, 2009; Fernando, 2011; Patnaik and Sharma, 2013). These authors note that the parameter estimates in a binary logistic regression are 1.6 to 1.8 times higher than they are in the probit model estimates. The studies do, however, find that despite the variances in the scaling of parameters, the estimators in the binary logistic and binary probit models nevertheless lead to the same standardised impacts of independent variables, and hence, similar results are obtained.

Fafchamps et al. (2017) employed a four-year (2005 to 2008) panel dataset on social networks comprising phone calls and airtime transfers to examine the influence of social network effects on mobile money adoption in Rwanda. Their study used outward bound airtime transfers as a proxy of mobile money adoption (dependent variable), while social network ties (family, friends and acquaintances) and the number of adopter network neighbours in a given week were the measures of the social network effects (independent variable). Fafchamps et al.'s (2017) study estimated the following linear probability model:

$$\Delta y_{it+1} = \alpha_1 + \alpha_2 \Delta A_{it} + \alpha_3 \Delta\left(S_{it}^2\right) + \alpha_4 \left(A_{it}^2\right) + \alpha_5 \Delta\left(S_{it} A_{it}\right) + controls + \Delta \varepsilon_{it+1} \tag{1}$$

where:

Δy_{it+1} is the likelihood that an airtime transfer was made by individual i at time t, with 1= success and 0 = no transfer;

t is the time measured in terms of a week;

ΔA_{it} is the number of neighbours of individual i who started sending airtime in week;

S_{it} is the number of weeks since individual i started using a SIM-ID, that is $S_{it} \equiv t - t_i$, and,

ε_{it} is the error term.

In rural Uganda, Murendo et al. (2015a) employed a cross-sectional survey of 477 households to investigate how social learning within a network influenced mobile money adoption in two districts (Kasese and Mukono). Their study estimated the following probit model:

$$MMA_i = X'_i \beta_1 + D_i \beta_2 + SN'_i \beta_3 + v_i \qquad (2)$$

where:

MMA is the observable binary discrete household mobile money adoption decision (where 1 = adoption, and 0 = non-adoption);

X'_i is the vector of control variables capturing household and contextual characteristics;

D_i is a vector of dummy variables accounting for unobserved variation across villages that could influence a household’s mobile money adoption decision;

SN'_i captures the social network effect, and,

v_i is the error term.

Murendo (2015a) used mobile money services (including airtime purchases, sending and receiving money, payments, insurance and credit) as a proxy for mobile money adoption. The number of exchange adopters and network structure proxies were used to represent the social network effects. The study's vector of control variables were age, gender, educational attainment of the household head, household size, distance to the nearest mobile money agent, wealth and asset ownership and access to information. The social network structure was proxied by the strength of ties (strong or weak ties) and network education status. The exchange adopters (the number of mobile money adopters in a household's social network with whom the household communicates and discusses mobile money) were used to measure the presence of social learning. The amount of land owned and off-farm income were the wealth proxies, while the number of mobile phones owned by the household, contact with a community knowledge worker and ownership of a radio and television set were measures of household information. Murendo et al. (2015a) classified a household as an adopter if any of its members had used mobile money technology in the year before their study.

Using the same cross-sectional survey data set obtained from the Kasese and Mukono districts in rural Uganda, Murendo et al. (2015b) followed the lead of Yau Fu et al. (2005) and Greene (2012) in estimating the following logistic regression model:

$$\prod_k(x)=\frac{\exp\left(\beta_{0k}+\beta_x^{'}\right)}{1+\exp\left(\beta_{0k}+\beta_x^{'}\right)} \qquad (3)$$

where:
k represents a country's provinces 1, 2, 3… K;

$\prod_k(x)$ is the likelihood that household will adopt mobile money;

β_{0k} stands for a nuisance or incidental (province specific) parameter, with constant contribution in the k^{th} province. The province-specific parameters β_{0k} (= 1, 2… k) are eliminated from the likelihood by conditioning on the number of positive outcomes in each province, and,

$\beta' = (\beta_1, \beta_2, \beta_3, \ldots, \beta_N)$ are the slope coefficients with respect to covariates, $X = (X_1, X_2, X_3, \ldots, X_N)$.

Lasserre (2015) employed a cross-sectional survey to investigate the effects of social networks on the adoption and variety of use of mobile money services in urban Uganda. The study estimated a logistic regression model, in which mobile money adoption (the dependent variable) was proxied by the use of mobile money services, and while social network effects (the independent variable) were measured by the reported number of social network exchange adopters' proxied social network effects. In order to control for possible confounding effects, Lasserre (2015) used income, English literacy, first use of mobile money, network size, personal innovativeness, perceived risk, mobile phone skills, perceived usefulness and perceived ease of use as control variables. The study proxied income by the amount of money an individual periodically received, while a single self-report question on one's ability to read English was used as a measure of English literacy. First use of mobile money services was proxied by the year of initial use and social network size was measured by the number of unique contacts mentioned by a respondent. The questions probing respondents' interest in new technologies and security concerns, adapted from Kim et al. (2010) were used as proxies of personal innovativeness and perceived risk respectively. Mobile phone skills were measured by a 12-item list based on the Actual Digital Skills questionnaire developed by the European Computer Driving Licence (ECDL, 2009).

A study by Kikulwe et al. (2014) employed household panel survey data to analyse the determinants mobile money adoption in rural Kenya. Their study estimated the following probit regression model:

$$MM_{it} = \alpha + \beta X_{it} + \delta T_t + \varepsilon_{it} \tag{4}$$

where:

MM_{it} is a dependent variable represented by a dummy that takes a value of 1 if household i has used mobile money services in year t, and 0 otherwise;

X_{it} is a vector of control variables that may influence the decision to use mobile money technology. The vector of control variables consisted of wealth, household, contextual, and agro-ecological condition effects. Kikulwe et al. (2014) proxied the neighbourhood effects by the percentage of households using mobile phones at village level, while wealth was measured farm size; the household size, gender, age, and education of the household head represented household characteristics;

T_t is a year dummy to control for time fixed effects, and,

ε_{it} is a random error term with a standardised normal distribution.

Table 4.1 below summarises the methodologies that were used by the empirical researchers discussed above, whose work focused on topics similar to those covered in the current study.

Table 4.1: A Summary of methodologies used in related studies

Empirical researcher and research design employed	Regression estimation used	Proxies of dependent and independent variables used
Fafchamps et al. (2017) Panel data	Linear probability model	Used outward bound airtime transfers as a proxy of mobile money adoption, while social network ties (family, friends and acquaintances) and the number of adopter network neighbours in a given week measured social network effects.
Murendo et al. (2015a)	Conditional probit	The use of mobile money

Cross-sectional survey	model	services as a measure of mobile money adoption. Number of exchange adopters, strength of ties and network education status used as proxies of social network effects.
Murendo et al. (2015b) Cross-sectional survey	Conditional (fixed effects) logistic regression model.	Employed the use of mobile money services as a proxy of mobile money adoption proxy. Number of exchange adopters, strength of ties and network education status used as proxies of social network effects.
Lasserre (2015) Cross-sectional survey	Logistic regression model.	The use mobile money services proxied mobile money adoption. Reported number of social network exchange adopters proxied social network effects
Kikulwe et al. (2014) Panel survey	Probit regression model	Use of mobile money services used as a mobile money adoption proxy. Neighbourhood (social network effects) measured by mobile phone usage

Source: Author’s compilation

4.3 RESEARCH DESIGN

The present study focuses on two countries – South Africa and Zimbabwe, which have very different levels of financial inclusion, internet penetration and social media use. The secondary data used for the study were obtained from individual responses in the cross-sectional FinScope consumer surveys South Africa 2015 and Zimbabwe 2014, which were conducted and reported by FinMark Trust (2015; 2014). FinMark Trust is an independent trust established in South Africa in 2002 with main funding provided by the United Kingdom's Department for International Development (DFID). The core purpose of FinMark Trust is to make financial markets work for the poor by promoting financial inclusion and regional financial integration using evidence-based information. FinMark Trust developed the FinScope survey, which is a nationally representative survey research tool to investigate how adult individuals source their income and manage their financial lives. In addition, the FinScope survey tool provides insights into adults' attitudes and perceptions regarding financial products and services in identified countries. The FinScope survey has achieved extensive reach over time, and to date, these surveys have been conducted in 26 countries, that is 13 states from the Southern African Development Community (SADC), six from non-SADC Africa and seven in Asia.

The present study chose the FinScope consumer surveys as the source of secondary data because for several reasons (FinMark Trust 2015; 2014). First, these consumer surveys are comprehensive and nationally representative of how individual people source their income and manage their financial lives. Second, they determine the systemic limitations that prevent financial markets from reaching out to unserved and under-served consumers through evidence-based outcomes. Third, the FinScope surveys are highly credible as they assist in establishing credible benchmarks and indicators of financial inclusion, while at the same time providing insights into market obstacles to growth and highlighting opportunities for policy reform and innovation in product development and delivery. Fourth, the findings of the FinScope surveys are extremely valuable to various stakeholders in providing effective policy guidance on improved financial products, markets and increased financial inclusion. Fifth, the data obtained from the surveys allow for cross-country comparisons and the sharing of mobile money adoption findings. Sixth, the FinScope consumer survey research tool is dynamic in nature as the survey content is evaluated every year to ensure that the most recent financial market trends are addressed and taken into consideration. Seventh, the FinScope surveys cover the most recent period when mobile money innovations were well established across countries, therefore data for all proxies used in the study are readily available for South Africa and Zimbabwe.

The objectives of the FinScope South Africa 2015 and Zimbabwe 2014 consumer surveys were four-fold. Firstly, they sought to ascertain the levels of financial inclusion through the proportion of the population using financial products and services (formal and informal). Secondly, the surveys described the landscape of financial access by the types of products and services used by financially included individuals. Thirdly, they sought to identify the drivers of, and barriers to the usage of financial products and services. Fourthly, the consumer surveys stimulated evidence-based research work, which ultimately led to effective stakeholder participation for deepened financial inclusion.

In the FinScope South Africa 2015 consumer survey, the universe was defined as all South Africans aged 16 years and older. A total of 5 000 face-to-face interviews were conducted between 14 July and 2 September 2015. The final respondent for the survey was randomly selected from a list of all qualifying individuals within a given household using a Kish Grid. The survey sample is nationally representative, with the appropriate sample frame and data weighting undertaken and benchmarked to the Statistics South Africa (Stats SA) 2015 mid-year population estimates. The data are statistically reliable and were validated.

The FinScope Zimbabwe 2014 consumer survey defined its universe population as all Zimbabweans aged 18 years and older. A total of 4 000 face-to-face interviews were conducted between July and September 2014. The respondents for the interview were randomly selected through use of the Kish Grid after listing all individuals aged 18 and above with their ages, income status and gender from each household. The sampling frame, quality control and weighting of the data were undertaken by the Zimbabwe National Statistics Agency (ZIMSTAT). The sample is a nationally representative individual-based sample of Zimbabwean adults, and the data are statistically reliable and were validated. Permission to access and use the FinScope South Africa 2015 and Zimbabwe 2014 consumer survey secondary data sets was sought from and granted by FinMark Trust prior to their use and ethical clearance was obtained. The certificate is attached as Appendix 1.

4.4 MAIN VARIABLES USED IN THE STUDY

The FinScope South Africa 2015 consumer survey questionnaire (Refer to Appendix 2) captured data on the household structure together with individual responses on spending habits, remittances, use of cell phones for financial services and technology, bank penetration, borrowing, insurance, retirement, savings, general attitudes and demographics. The FinScope Zimbabwe 2014 consumer survey questionnaire (Refer to Appendix 3) captured data on household information and demographics, technology connectivity, access to infrastructure, farming and off-farm activities together with individual responses on income, expenditure and remittances, financial literacy, money management (saving, investment and borrowing), insurance, bank penetration, mobile money, informal activities and general perceptions. Table 4.2 below shows the extracted variables, proxies used, and the sources of the questions for the extracted variables.

Table 4.2: Study variables, proxies used and sources

Variable	Proxy Used	Source from FinScope South Africa 2015 questionnaire Appendix 1	Source from FinScope Zimbabwe 2014 questionnaire Appendix 2
Mobile money adoption	Payments, insurance, savings, remittances, credit using a cell phone	Question C3, D3, D7	Question 1.23, 1.34, 2.5, 3.1, 3.8, 3.17, 3.34, 3.41, 5.6, 6.3a, 7.5b, 8.16, 8.23
Social media	Ownership of telecommunication	Question E1, E5	1.33a, 1.34

	devices; Use of the internet through online platforms (Facebook, MXit, Twitter, Instagram, BBM and WhatsApp)		
Age	Respondent’s age in years	Household register.	Question 1.2 on household head, introduction and screening sheet for respondent selection (if selected respondent is not the household head); 10.7
Gender	Respondent’s gender	Household register	Questions 1.2 on household head; introduction and screening sheet for respondent selection (if selected respondent is not the household head), 10.6
Marital Status	Respondent’s marital status	Question M2	Question 1.9
Education	Respondent’s	Question M3	Question 1.10

	educational attainment		
Employment status	Respondent’s employment status	Question M4	Question 1.11
Household size	Number of people in household	Household register.	Question S1 on introduction and screening sheet for respondent selection.
Household Location	Location of dwelling (rural/urban)	Household register section (page 3).	Respondent information page 1 section 1.A
Income	Respondent’s personal monthly income	Question M6a, M6b	Question 3.12a, 3.12b
Access to information	Ownership and or access to radio, television sets, satellite decoders, cell phones, newspapers, magazines	Question M5	Question 1.31, 1.33, 1.35
Bank account ownership	Respondent’s own bank account	Question F1	Question 8.4

Source: Author’s compilation

While the present study investigates mobile money adoption in developing countries similar to Fafchamps et al. (2017), Murendo et al. (2015a; 2015b), Kikulwe et al. (2014), Lasserre (2015) and Munyegera and Matsumoto (2014) in East Africa, its approach differs in a number of ways. Firstly, instead of the narrow-reaching physical social networking, the current study explores the likely influence of social media on mobile money adoption that is intermediated through the internet which offers immediacy of information diffusion. Secondly, a comparative analysis of South Africa and Zimbabwe is undertaken based on the countries' differences with regard to mobile money adoption, social media penetration and the social media-mobile money adoption nexus.

A comparison between the two countries provides information on the impact use of social media on mobile money adoption. The current study therefore provides a novel approach towards accelerated financial inclusion in developing countries. The study assumed that individuals selected in the FinScope South Africa 2015 and Zimbabwe 2014 consumer surveys patronised at least one of the identified social media platforms or proxies that is Facebook, Twitter, WhatsApp, Instagram, MXit, e-mail on tablets, desktops, laptops or accessed the internet using cell phones. A summary of the theory a priori and expected signs of the variables extracted from the FinScope South Africa 2015 and Zimbabwe 2014 consumer surveys is provided in Table 4.3 below.

Table 4.3: Summary of variables' theory intuition and expected signs

Variable	**Theory Intuition and Source**	**Expected Sign**
Social media	Social media use positively influences financial behaviour (Nyagucha, 2017; Kosavinta et al., 2017; Kavitha and Bhuvaneswari, 2017; Beier and Wagner, 2015; Heimer, 2016; Mudholkar and Uttarwar, 2015).	+
Interaction term (Use of social media × Mobile money adoption)	Interaction term significantly increases overall mobile money adoption. (Author)	+
Gender	Males are more likely than females to adopt mobile money services (Demirgüç-Kunt et al. 2018; Biscaye et al. 2017; FinMark Trust, 2016 Badinenko, Barasinska, and Schafer, 2011; Kara, Mishra and Dash, 2010).	+

Age	The younger population is more likely to adopt mobile money technology compared than older people (Maheshwari and Mittal, 2017; Gamble et al., 2015; Choi et al., 2014; Jain and Mandot, 2012; Onsomu, 2015; Lachs and Han, 2015; Korniotis and Kumar, 2011; Agarwal, 2009).	-
Education	Educated people are more likely to adopt mobile money services (FinMark Trust, 2016; Lasserre, 2015; Kikulwe et al., 2014; Munyegera and Matsumoto, 2014; Chattopadhyay and Dasgupta, 2015).	+
Marital status	The married are more risk averse than the single and will not undertake some financial behaviour (Chattopadhyay and Dasgupta, 2015; Arano, Parker and Terry, 2010). Marriage increases the likelihood of financial participation (Christiansen et al., 2015). Marital status has no effect on financial investment decisions (Dayioglu and Gumus, 2015).	+/-
Household size	Large households are more likely adopt mobile money technology (Murendo et al., 2015a; 2015b; Lasserre, 2015; Kikulwe et al., 2014)	+
Household location	Urban households are more likely to adopt mobile money services than their rural counterparts (GSMA, 2014; Lwanga and Adong, 2016; Intermedia,	+

	2013; Marumbwa and Mutsikiwa, 2013).	
Access to information	Access to information increases mobile money adoption (Murendo et al., 2015a; 2015b).	+
Bank account ownership	Bank account ownership reduces mobile money adoption (FinMark Trust, 2016).	-
Employment	The unemployed are more likely to adopt mobile money adoption than the employed (FinMark Trust, 2016). The employed are capacitated to participate in financial activities, and take on more risks (Chattopadhyay and Dasgupta, 2015; Jain and Mandot, 2012).	+/-
Income	Higher income increases mobile money adoption (FinMark Trust, 2016; Murendo et al., 2015a; 2015b; Lasserre, 2015). Increased income negatively affects financial decision making Faff et al., (2008).	+

Source: Author's compilation

4.5 ESTIMATION MODEL

The study employed the binary logistic regression model for the main estimation to examine the impact of social media use on mobile money adoption behaviour. The use of the binary logistic regression model in the main econometric estimation is consistent with closely related empirical literature on social networks and mobile money adoption (Murendo et al., 2015b; Lasserre, 2015), and is compatible with the available cross-sectional data from the FinScope South Africa 2015 and Zimbabwe 2014 consumer surveys. The binary logistic model's superiority is also based on greater robustness of results, flexibility, simplicity, the fact that is not necessary to make any assumption about the distribution of the independent variables as they need not be normally distributed, that independent variables need not be linearly related to the dependent variable or of the same variance within the same category, the ability to handle qualitative data, interaction terms and analytical convenience from direct interpretation of results (Makina, 2012; Greene, 2012; Fox, 2010; O'Connell, 2011; Mudiwa, 2011; Wittink, 2011, Wilson and Lorenz, 2015). Since mobile money adoption (dependent variable) is dichotomous in nature, the objective then was to find the probability of an individual choosing to use mobile money services. The dichotomous nature of mobile money adoption is expressed as follows:

$$\text{Mobile money adoption} = \begin{cases} 1 \\ 0 \end{cases} \tag{5}$$

where:

1 = success if an individual uses mobile money services, and

0 = failure if an individual does not use mobile money services.

The binary logistic equation as advanced by Greene (1993) adopted in this study is as follows:

$$\Pr(Y=1) = \frac{e^{\beta^{'} X}}{1+e^{\beta^{'} X}} \quad , \tag{6}$$

with the cumulative distribution function given by

$$F(\beta^{'} X) = \frac{1}{e^{\beta^{'} X}} \quad , \tag{7}$$

where $\beta^{'}$ represents the vector of parameters associated with the independent variables represented by X.

Following equation (6) above, the binary logistic model which employs an interaction term (where an individual was both an adopter of mobile money technology and used social media) was estimated in order to analyse how overall mobile money adoption would be increased. The binary logistic model estimated for the study is therefore specified as:

$$\text{Mobile Money Adoption}_i = \beta_0 + \beta_1 \text{SocMed}_i + \beta_2 \text{SocMedia}_i \times \text{Mobile Money Adoption}_i + \beta_3 X_i + \varepsilon_i \quad (8)$$

where:

Mobile Money Adoption_i is the dependent variable with a binary outcome where 1 = if an individual i adopts mobile money technology, and 0 = non-adoption of mobile money technology by an individual;

SocMedia is the respondent's use of social media, with an expected positive sign consistent with related literature (Mudholkar and Uttarwar, 2015; Siganos et al., 2014; Beshears et al., 2015; Ammann and Schaub, 2016);

Mobile Money $\text{Adoption}_i \times \text{SocMedia}_i$ captures how the overall mobile money adoption would be increased by the simultaneous adoption of mobile money technology and use of social media effect, that is, an individual must use mobile money as well as social media, Mobile Money $\text{Adoption}_i \times \text{SocMedia}_i$ is therefore an interaction term, with an expected positive sign inferred from related social media-financial behaviour nexus literature (Mudholkar and Uttarwar, 2015; Siganos et al., 2014; Beshears et al., 2015; Ammann and Schaub, 2016);

X_i is a vector of the critical control variables to be parsimoniously determined, and

ε_i is the error term.

4.5.1 Model diagnostics

Following the estimation of the binary logistic regression model parameters using the maximum likelihood estimator, it was essential to evaluate the significance of the use of social media, the interaction term and control variables with regard to predicting an individual's adoption of mobile money services. As in Harrell (2001), there were a number of statistics that were used for such an evaluation - the odds ratio, pseudo

R^2 equivalents, log-likelihood ratio, omnibus test of model coefficients, Hosmer-Lemeshow goodness of fit, classification table and Wald test.

4.5.1.1 Odds ratio

The binary logistic model estimation measures the link between the dichotomous dependent variable (mobile money adoption) and the predictors (social media and control variables) using the odds ratio. Hosmer and Lemeshow (1989) explain that the odds ratio refers to a measure of association between the binary outcome and an independent variable that provides a clear indication of how the risk of the outcome being present changes with the variable in question. Therefore, the odds ratio is the likelihood that an event will occur (an individual's adoption of mobile money technology) divided by the probability that it will not (non-adoption). O'Connell (2011) observes that the odds ratios are bounded below by 0 but have no upper bound, thus, the odds ratio can range from 0 to infinity. The odds ratio formula that indicates whether the chances of a success case are equal to those of failure is given by:

$$\text{Odds Ratio} = \frac{\text{Odds of Case}}{\text{Odds of Non-Case}} \qquad (9)$$

Strong associations between independent variables and the outcome are typically represented by odds ratios further from 1 in either direction. A value less than 1 indicates that a unit increase in an independent variable, holding other variables constant, will result in the outcome less likely to occur; a value greater than 1 indicates that a unit increase in the independent variable holding other variables constant will lead to a high likelihood of occurrence of the outcome (Muchabaiwa, 2013). The statistical significance of an odds ratio is typically analysed by testing whether the regression coefficient, β, is statistically different from zero through any one of the Wald, score, or likelihood ratio tests.

4.5.1.2 R^2 Equivalents for logistic regression

One way of evaluating the effectiveness of a regression model is to calculate a statistic which measures how strong the relationship between the explanatory variable(s) and the outcome is (Kleinbaum and Kein, 2010). This statistic is represented by the R^2 measure in linear regression analysis. However, Greene (2008) and Harrell (2001) note that in modelling binary or other discrete choices there is no direct counterpart to the R^2 goodness of fit statistic as is applied in linear regression in assessing the predictive power of a model. Instead, a pseudo R^2 whose value is similar to the R^2 in multiple regression is estimated. The pseudo R^2 in binary logistic regression lies between “0” and “1”, with a value of “1” indicating that the fitted model accounts for 100% of variance in the dependent variable (outcome), while a value “0” means that it explains none of the variance (ibid). The R^2 measure for binary logistic using the IBM SPSS is estimated by the Cox and Snell (1989) R^2. Hosmer and Lemeshow (2000) observe that the value of the Cox and Snell Pseudo R^2 cannot reach 1. Nagelkerke (1991), however, improved it to reach 1; a value of 1 is an indication of a perfect fit whilst a value of zero is an indication that there is no relationship, thus, the higher the R^2 value the better fit of the model.

4.5.1.3 Log-likelihood Ratio

The Log-likelihood ratio is a statistical measure used in comparing the goodness of fit of two estimated models - that is the null model with just the constant (β_0), and a full model after addition of independent variables. Muchabaiwa (2013) argues that a decline in the Log-likelihood ratio from the null to the full model is an indicator of improved goodness of fit of the model.

4.5.1.4 Omnibus Test of model coefficients

The Omnibus test statistic is a measure of the overall model fit. Lawrence, Gamst, and Guarino (2006) and Muchabaiwa (2013) note that the Omnibus Test statistic is comparable to the F-test in linear regression. Thus, the null hypothesis is to be rejected if the obtaining p-value of the Omnibus test of model coefficients is less below 0.05 (significance level). A significant test statistic suggests that the binary logistic regression is an adequate fit, and can therefore be used to model the observed data (ibid).

4.5.1.5 Hosmer-Lemeshow goodness of fit

An alternative method for assessing model fitness is the Hosmer-Lemeshow goodness of fit test. This statistic compares the predicted values against the actual values of the dependent variable. The Hosmer-Lemeshow goodness of fit test is comparable to the chi-square test and forms several groups referred to as deciles of risk based on the estimated probabilities for the sample (O'Connell (2011). A good fit model will have a small Hosmer-Lemeshow test statistic and a p-value that is greater than the 0.05 significance level (Hosmer and Lemeshow, 1989; 2000).

4.5.1.6 Classification table

A classification table also measures the predictive accuracy of a binary logistic regression model (Muchabaiwa, 2013). This method involves cross classifying the dependent variable y with the categorical variable coming from the fitted logistic probabilities ($\hat{y}$). The percentage of successes that have been correctly classified as such is referred to as the sensitivity of the model, while the percentage of failures that have been correctly classified is the specificity of the model (ibid). The failures that are incorrectly classified as success are referred to as false positive and the success that are incorrectly classified as failures are referred to as false negatives (Sharma, 1996). Table 4.4 below shows a typical classification table.

Table 4.4: Classification Table

		Predicted		
		Mobile Money Adoption Decision		
		Yes (success)	No Adoption (failure)	Percentage Correct
Mobile Money Adoption Decision	Yes (success)	a	b	$\frac{a}{a+b}(100)$
	No Adoption (failure)	c	d	$\frac{d}{c+d}(100)$
	Overall Percentage			$\frac{a+d}{a+b+c+d}(100)$

Source: Author's compilation

In table 4.4 above, the ratio $\frac{a}{a+b}(100)$ is the specificity of the model, and $\frac{d}{c+d}(100)$ is the sensitivity of the model. High values for specificity and sensitivity are an indication of a good fit of the model (Muchabaiwa, 2013). Kutner et al. (2005) argue that if a model fitting sample produces the same prediction error rate as the validation sample, then the fitted model will be reliable.

4.5.1.7 Wald test

The Wald statistic is employed to evaluate the significance of individual logistic regression coefficients, specifically whether the explanatory variable's coefficient is significantly different from zero. The parameter estimate for the effect of each independent variable in a binary logistic model (the Wald test) is divided by its respective standard error, and the results are squared to represent a value from the chi-square distribution with one degree of freedom under the null hypothesis of no effect (O'Connell, 2011). IBM SPSS reports the Wald test chi-square statistics for each variable in the fitted model. The Wald statistic is chi-square distributed with 1 degree of freedom. The null hypothesis is to be rejected if the p-value of the Wald test is below 0.05 (significance level) - a coefficient with a p-value which is less than 0.05 implies that the variable is significant in the model (Muchabaiwa, 2013).

4.6 ROBUSTNESS CHECKS

This study followed the lead of Murendo et al. (2015a) and Kikulwe et al. (2014) in estimating an additional model for robustness checks using a binary probit link function. Estimation using the binary probit model is also supported by other empirical studies, which have shown that qualitatively, the binary logistic and binary probit model estimations often produce very similar results (Fenella, 2016; Lewbel et al., 2012; Verbeek, 2004; Park, 2009; Fernando, 2011; Patnaik and Sharma, 2013 Cakmakyapan and Goktas, 2013; Greene, 2012). The binary probit model estimated for robustness checks in the study is shown below:

$$\text{Mobile Money Adoption}_i = \beta_0 + \beta_1 \text{SocMed}_i + \beta_2 \text{SocMedia}_i \times \text{Mobile Money Adoption}_i + \beta_3 X_i + \varepsilon_i \quad (10)$$

where:

Mobile Money Adoption_i is the observable binary discrete choice of whether or not an individual adopts mobile money technology;

SocMed_i is the use of social media, which consistent with extant literature (Mudholkar and Uttarwar, 2015; Siganos et al., 2014; Beshears et al., 2015; Ammann and Schaub, 2016) is expected to have a positive sign;

X_i is the vector of control variables which are to be parsimoniously determined through the principal component analysis procedure;

Mobile Money $\text{Adoption}_i \times \text{SocMedia}_i$ captures how the overall mobile money adoption would be increased by the simultaneous adoption of mobile money technology and use of social media effect, that is, an individual must use mobile money as well as social media. Mobile Money $\text{Adoption}_i \times \text{SocMedia}_i$ is therefore an interaction term, with an expected positive sign inferred from related social media-financial behaviour nexus literature (Mudholkar and Uttarwar, 2015; Siganos et al., 2014; Beshears et al., 2015; Ammann and Schaub, 2016);

βs are the parameters to be estimated, and

ε_i is the error term.

4.7 MODEL LIMITATIONS

Train (2010) observed two additional features of the binary logistic model, which are both merits and demerits of the model. Firstly, despite the binary logistic model being able to represent systematic taste variation very well, it nevertheless fails to represent random taste variation. Secondly, if the unobserved factors are independent over time in repeated choice situations, the logistic model can capture the dynamics of repeated choice. This ability of the binary logistic model is restrictive, however, as it indicates substitution patterns. Thirdly, despite being a generally quick, easy and cost effective means of data collection, cross-sectional survey data are deficient in the richness offered by longitudinal surveys such as trends observed on the same respondents (Sedgwick, 2014). As a result, the estimation model employed in this study is static; it suffers from a lack of dynamism arising from changes observed over time. The binary logistic model therefore does not reveal the sequential association between variables and an outcome, and thus, only an association and not absolute causation can be inferred from a cross sectional study.

4.8 CHAPTER SUMMARY

This chapter discussed the process of establishing an appropriate method for predicting an individual's choice to adopt mobile money technology. A suitable research design and econometric approaches used to address the objectives articulated in the introductory chapter was developed. The type, sources, proxies, credibility, extraction and limitations of the data used in the study were provided. The methodologies used to model discrete binary data, those employed in closely-related empirical studies and the improvements contributed by the current study were discussed. Motivation was provided for the choice of the maximum likelihood estimation technique employed in the logistic regression as the main data analysis model. The model fit measures such as the Odds ratio, Wald Test, Hosmer and Lemeshow Test, and the Classification Table, which are employed to assess how adequately the logistic model fits the data for the current study were discussed. The binary probit model was employed for robustness checks to confirm whether it would achieve similar results to the binary logistic estimation. The following chapter employs descriptive statistics to interpret the preliminary results of the study in a comparison of South Africa and Zimbabwe.

CHAPTER 5

DESCRIPTIVE ANALYSIS AND FINDINGS

5.1 INTRODUCTION

This chapter presents the preliminary findings of the study using descriptive statistics, graphs and tables. The FinScope South Africa 2015 and Zimbabwe 2014 consumer survey data sets are analysed and comparisons between the two countries are made, with regard to the use of social media, mobile money adoption and the probable link between them. The rest of this chapter is organised as follows: section 5.2 discusses the overall descriptive statistics of the two countries. Section 5.3 compares the general use of social media, the determinants thereof and further presents a breakdown of the social media platforms used in South Africa and Zimbabwe. Section 5.4 focuses on mobile money adoption in the two countries, its determinants and the differences between them. Section 5.5 examines the relationship between the use of social media and mobile money adoption in South Africa and Zimbabwe, and finally, section 5.6 concludes the chapter.

5.2 DESCRIPTIVE STATISTICS

The descriptive statistics from the preliminary findings for South Africa and Zimbabwe involved reducing the data into four statistics: minimum, maximum, mean and standard deviation. These are presented in Table 5.1 below.

Table 5.1: Descriptive statistics of South Africa and Zimbabwe

Descriptive Statistics:		SOUTH AFRICA N=4149				ZIMBABWE N= 3750			
Variable Name	**Description**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**
HH.Loc	Household Location: Rural or Urban area	0	1	0.77	0.419	0	1	0.34	0.473
HH.Size	Number of adults	1	24	3.03	1.867	1	10	4.61	2.079
Age	Age of Respondent	16	99	39.90	15.24	18	85	40.00	15.78
Gender	Respondent Gender	0	1	0.45	0.497	0	1	0.43	0.495
Marital Status	Respondent is single or otherwise	0	1	0.55	0.498	0	1	0.14	0.348
Monthly Income	Respondent's Actual Monthly Income	R0	R90 000	4820.6	6432	$0	$21501	$167	$736
Education	Respondent's Educational Attainment : Primary or Secondary	0	1	0.90	0.303	0	1	0.61	0.487
Employment	Respondent's Employment Status: Unemployed or Employed	0	1	0.54	0.498	0	1	0.95	0.226
Bank Acc.	Respondent's Bank Account Ownership	0	1	0.69	0.462	0	1	0.18	0.383

Infor. Access	Respondent has access to information or not	0	1	1.00	0.000	0	1	0.94	0.243
Social Media Use	Respondent uses social media or not	0	1	0.45	0.498	0	1	0.26	0.439
MMA	Respondent uses mobile money services or not	0	1	0.014	0.119	0	1	0.49	0.500

Source: Author's compilation

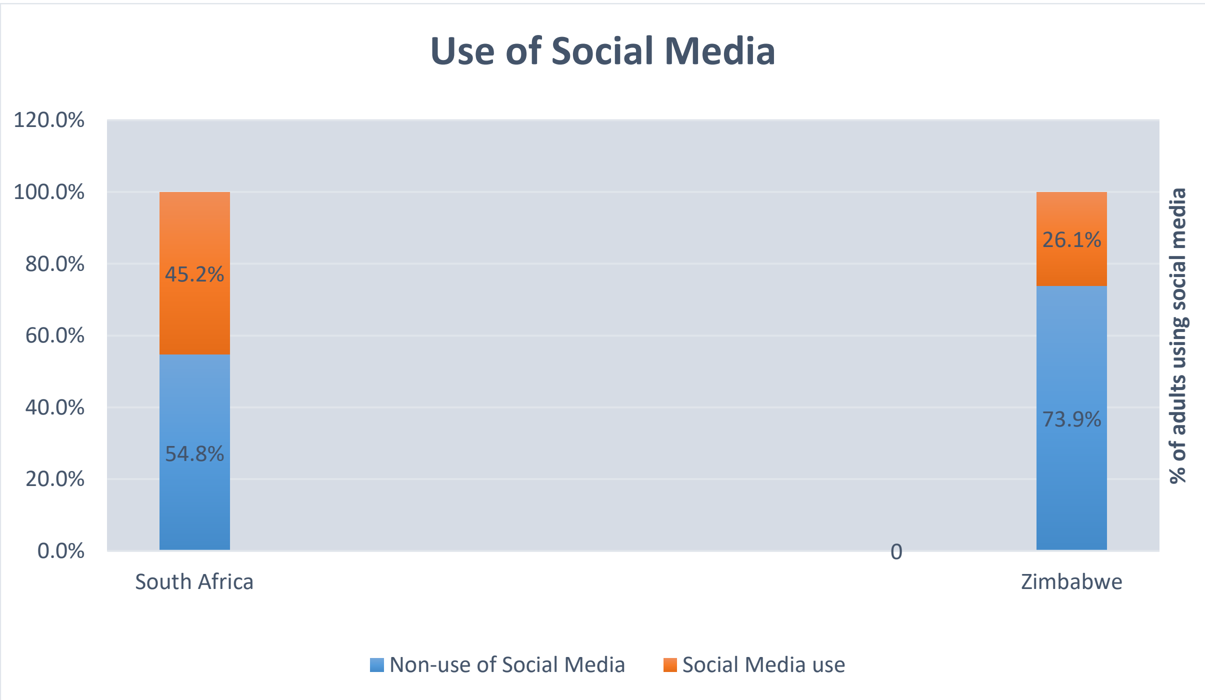
While not conclusive, the descriptive statistics from the preliminary results in Table 5.1 above reveal that nine variables were dummies, and hence have minimum values of 0 and maximum values of one. Among the ordinal variables, the level of personal monthly income exhibits high volatility. Household location reveals that South Africa was highly urbanised, as 77% of the adult population resided in the urban areas compared to Zimbabwe's 34%. Household size shows that Zimbabwe had a higher average number of household members per household (4.61) than South Africa (3.03). With respect to the average respondent age, there was a very small variation between the two countries; they were almost at par (39.9 years for South Africa and 40 years for Zimbabwe). Gender-wise, there were more women than men in both countries as evidenced where males constituted 45% and 43% of the total adult population in South Africa and Zimbabwe respectively.

The preliminary findings revealed a marked difference in terms of the marital status of adults in the two countries as 55% of South African adults were single compared to 14% in Zimbabwe. A comparison of personal monthly income showed that on average, a South African adult had a higher amount (R4820.56), while their Zimbabwean counterpart had an amount equivalent to R2502.90 (that is US$166.86 *15 according to Stats SA 2015 year end exchange rate). Preliminary data analyses also indicated that 90% of the adults in South Africa had attained secondary education and above, compared to 61% in Zimbabwe. A total of 54% of the adult population in South Africa are employed in comparison to 95% in Zimbabwe. However, these statistics concealed marked differences between the two countries wherein there was actually high formal employment in the South Africa than Zimbabwe where the seemingly high employment rate was driven mainly by informal entrepreneurs. The FinScope South Africa 2015 and Zimbabwe 2014 surveys made no specific reference to whether the respondent was formally or informally employed, hence the difference in the countries' employment rates. South Africa had 51% more banked adults than Zimbabwe. South Africa had a higher information access rate (100%) than Zimbabwe (94%) as indicated by household ownership of cell phones, radio and television sets, satellite decoders, access to local radio, newspapers and magazines.

5.3 USE OF SOCIAL MEDIA

The FinScope South Africa 2015 and Zimbabwe 2014 consumer survey data sets were analysed in order to determine the social media penetration levels in the two countries. These are shown in Figure 5.1 below.

Figure 5.1: Social media penetration in South Africa and Zimbabwe



Source: Author's compilation

The results in Figure 5.1 above show a higher level of social media usage in South Africa (45.2%) than Zimbabwe (26.1%). The preliminary outcome is similar to findings by World Wide Worx (2017) and Hootsuite (2017), who found that social media penetration rates in South Africa were mainly driven by declining costs of mobile phone devices and internet data costs, leading to a growth in downloads of social media applications. QWERTY (2017) reports that nearly 70% of South Africans' weekly internet activities were spent on social media platforms alone. The report demonstrates the increasingly important role social media plays in the lives of the South African population. On the other hand, while the social media penetration rate in Zimbabwe is lower, the Postal and Telecommunications Regulatory Authority of Zimbabwe (POTRAZ, 2018) notes that the growth in usage was largely due to increased mobile phone penetration (102.7%) and lower data tariffs. Mobile devices accounted for 95.6% of internet access traffic in Zimbabwe (POTRAZ, 2016).

5.3.1 Determinants of social media use

Although inconclusive, the results with regard to the determinants of social media use in South Africa and Zimbabwe are presented in detail in Tables 5.2 and 5.3 below and discussed thereafter.

Table 5.2: Determinants of social media use in South Africa

Determinant variables		Social media use in South Africa					
		Non-use of Social Media			Social Media use		
		N	% of Category	% of Total	N	% of Category	Percentage of Total
Household location	Rural: Traditional & Farms	860	31.7%	17.4%	259	11.6%	5.2%
	Urban	1850	68.3%	37.4%	1972	88.4%	39.9%
Household size	1	530	19.6%	10.7%	490	22.0%	9.9%
	2	679	25.1%	13.7%	570	25.5%	11.5%
	3	548	20.2%	11.1%	501	22.5%	10.1%
	4	387	14.3%	7.8%	384	17.2%	7.8%
	5	267	9.9%	5.4%	150	6.7%	3.0%
	6	146	5.4%	3.0%	73	3.3%	1.5%
	7	67	2.5%	1.4%	27	1.2%	0.5%
	8	36	1.3%	0.7%	21	0.9%	0.4%

	9	19	0.7%	0.4%	8	0.4%	0.2%
	10	9	0.3%	0.2%	4	0.2%	0.1%
	11	9	0.3%	0.2%	0	0.0%	0.0%
	12	7	0.3%	0.1%	1	0.0%	0.0%
	13	1	0.0%	0.0%	0	0.0%	0.0%
	14	1	0.0%	0.0%	0	0.0%	0.0%
	15	1	0.0%	0.0%	1	0.0%	0.0%
	17	1	0.0%	0.0%	0	0.0%	0.0%
	19	0	0.0%	0.0%	1	0.0%	0.0%
	21	1	0.0%	0.0%	0	0.0%	0.0%
	24	1	0.0%	0.0%	0	0.0%	0.0%
Gender	Female	1555	57.4%	31.5%	1182	53.0%	23.9%
	Male	1155	42.6%	23.4%	1049	47.0%	21.2%
Marital status	Other	1317	48.6%	26.7%	928	41.6%	18.8%
	Single	1393	51.4%	28.2%	1303	58.4%	26.4%
Educational attainment	Primary & no education	469	17.3%	9.5%	38	1.7%	0.8%
	Secondary & above	2241	82.7%	45.4%	2193	98.3%	44.4%
Employment status	Unemployed	1556	57.4%	31.5%	700	31.4%	14.2%
	Employed	1154	42.6%	23.4%	1531	68.6%	31.0%
Bank account ownership	No	1173	43.3%	23.7%	350	15.7%	7.1%
	Yes	1537	56.7%	31.1%	1881	84.3%	38.1%
Access to information (cell phones, radios, television sets, cable decoders, newspapers, magazines)	Household has no access to information.	0	0.0%	0.0%	0	0.0%	0.0%
	Household has access to information.	2710	100.0%	54.8%	2231	100.0%	45.2%

Source: Author’s compilation

Table 5.3: Determinants of social media use in Zimbabwe

Determinant variables		Non-use of Social Media N	Non-use of Social Media % of Category	Non-use of Social Media % of Total	Social Media use N	Social Media use % of Category	Social Media use % of Total
Household location	Rural	2111	76.2%	56.3%	368	37.6%	9.8%
	Urban	659	23.8%	17.6%	612	62.4%	16.3%
Household size	1	150	5.4%	4.0%	72	7.3%	1.9%
	2	227	8.2%	6.1%	102	10.4%	2.7%
	3	446	16.1%	11.9%	188	19.2%	5.0%
	4	545	19.7%	14.5%	210	21.4%	5.6%
	5	502	18.1%	13.4%	175	17.9%	4.7%
	6	355	12.8%	9.5%	102	10.4%	2.7%
	7	226	8.2%	6.0%	67	6.8%	1.8%
	8	147	5.3%	3.9%	34	3.5%	0.9%
	9	132	4.8%	3.5%	18	1.8%	0.5%
	10	40	1.4%	1.1%	12	1.2%	0.3%
	11	0	0.0%	0.0%	0	0.0%	0.0%
Gender	Female	1601	57.8%	42.7%	528	53.9%	14.1%
	Male	1169	42.2%	31.2%	452	46.1%	12.1%
Marital status	Other	2491	89.9%	66.4%	731	74.6%	19.5%
	Single	279	10.1%	7.4%	249	25.4%	6.6%
Educational attainment	Primary & no education	1332	48.1%	35.5%	115	11.7%	3.1%
	Secondary & above	1438	51.9%	38.3%	865	88.3%	23.1%
Employment status	Unemployed	143	5.2%	3.8%	60	6.1%	1.6%
	Employed	2627	94.8%	70.1%	920	93.9%	24.5%
Bank account ownership	No	2478	89.5%	66.1%	604	61.6%	16.1%
	Yes	292	10.5%	7.8%	376	38.4%	10.0%
Access to information (cell phones, radios, television sets, cable decoders, newspapers, magazines)	Household has no access to information	228	8.2%	6.1%	0	0.0%	0.0%
	Household has access to information.	2542	91.8%	67.8%	980	100%	26.1%

Source: Author's compilation

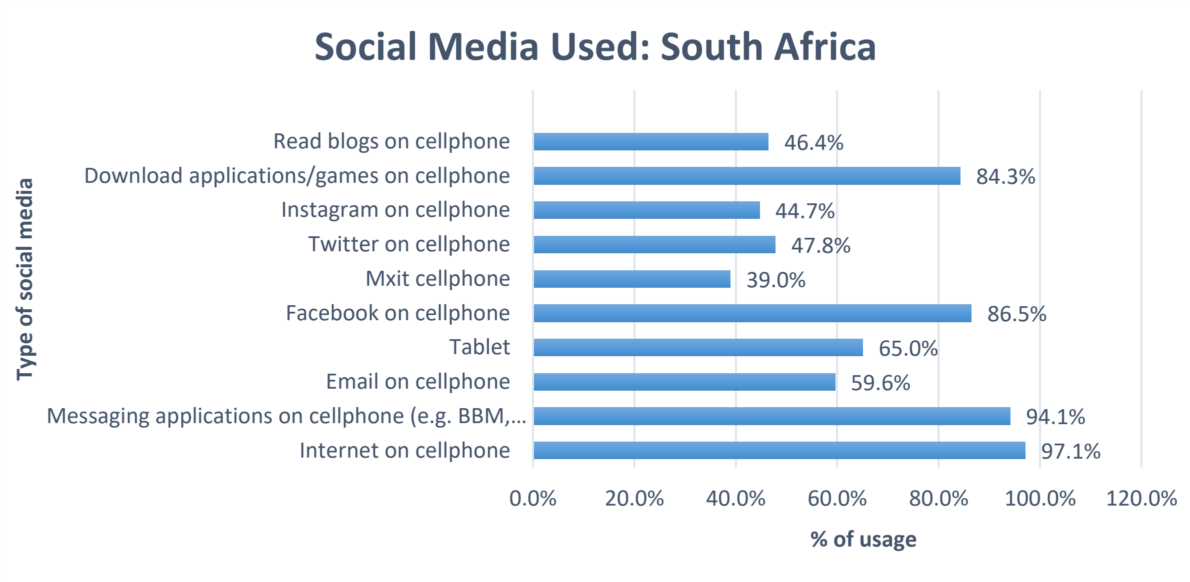
In South Africa, the descriptive statistics in Table 5.2 show that urbanites (88.4%) were more likely to use social media than their rural counterparts (11.6%), and the greatest proportion of users emerged from households with one to ten members (87.2%). Females (53%) were more likely to be users than males (47%); singles (58.4%) more likely than the “other” marital status category (41.6%); individuals aged 16 to 60 years (96.6%) were more likely to use social media than any other age ranges. With regard to socioeconomic factors, South African adults with secondary and higher education (98.3%) were more likely to use social media than those with primary education or none, thus accentuating the importance of general literacy in the use of social media platforms. Employed individuals (68.6%) were more likely to use social media platforms than the unemployed (31.4%); individuals with a personal monthly income ranging from R500 to R32 000 are more likely to be social media users than any other income category; the banked (84.3%) we more likely than the unbanked (15.7%). Individuals with access to information (100%) do use social media.

Likewise, in Zimbabwe, Table 5.3 shows that urbanites are more likely to use social media (62.4%) than those in rural areas (37.6%), possibly as a result of their increased access to information; households with ten members or less (77.6%) were more likely than those with more members. The indicative results also showed that females (53.9%) were more likely to be social media users than males (46.1%); the “other” marital category (74.6%) was more likely than singles (25.4%); individuals aged between 18 to 60 years (96.8%) were more likely than any other age group. Social media usage was more likely among individuals with secondary education or higher (88.3%) than those with primary or no education (11.7%); the employed were more likely (93.9%) than the unemployed (6.1%). Individuals who had a monthly income range of USD $51 (R765) to USD $1501 (R22 515) were more likely to use social media than any other income category; the unbanked (61.6%) were more likely to be than the banked (38.4%), as were individuals with access to information (98%) than those without (2%).

5.3.2 Types of social media channels used

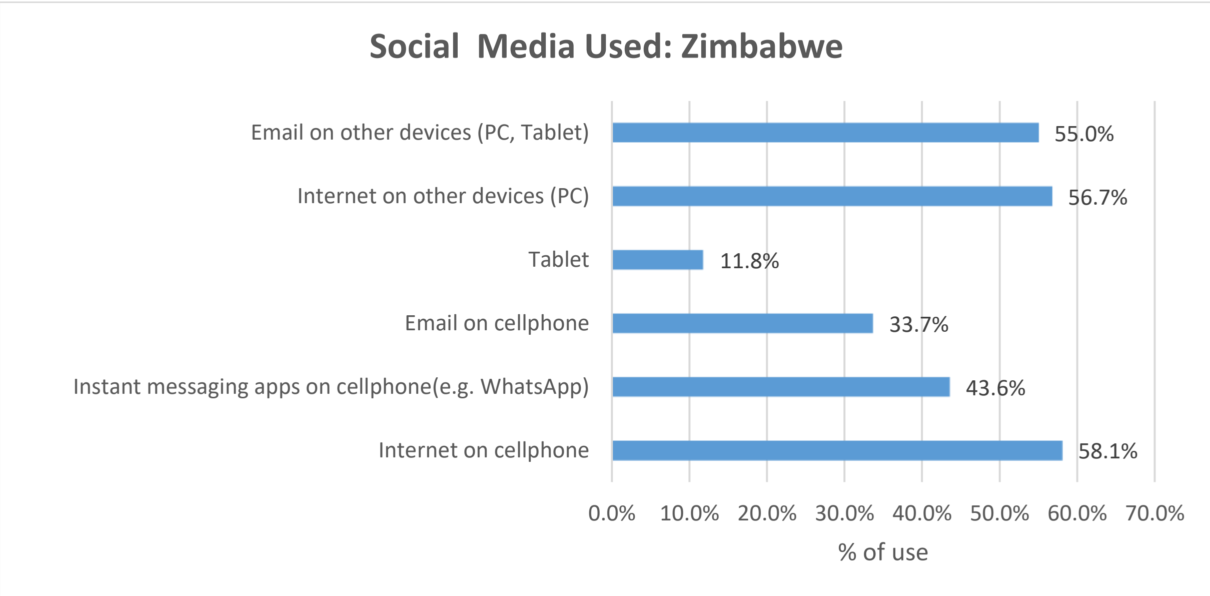
The FinScope South Africa 2015 and Zimbabwe 2014 consumer survey data sets were manipulated further in order to disaggregate the specific types of social media platforms used in each country and the results are presented below in Figures 5.2 and 5.3 respectively.

Figure 5.2: Types of social media channels used in South Africa



Source: Author's compilation

Figure 5.3: Types of social media channels used in Zimbabwe



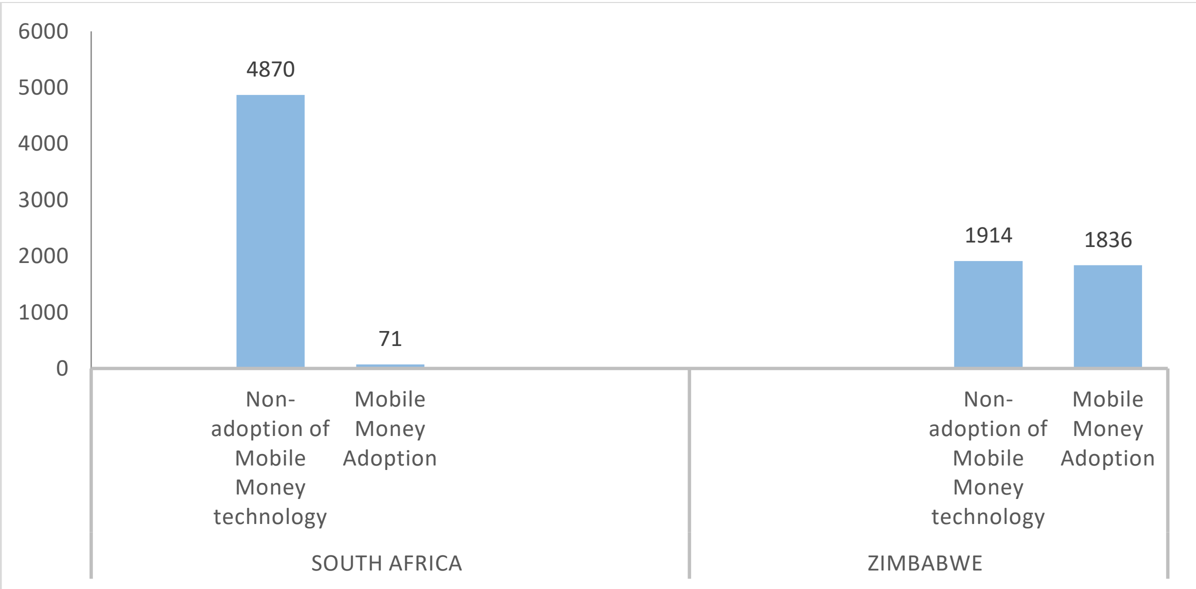
Source: Author's compilation

Preliminary results revealed that a wider range of social media platforms/channels were used in South Africa (11) than in Zimbabwe (7). While internet traffic in both countries was predominantly accessed through cell phones, there were more users in South Africa (97.1%) than Zimbabwe (58.1%). The rate of accessing the internet in South Africa using a tablet (65%) or email on a cell phone device (59.6%) was higher than in Zimbabwe (11.8% and 33.7% respectively). While the use of online instant messaging such as WhatsApp was popular in both countries, it was much higher in South Africa (94.1%) than Zimbabwe (43.6%). The results also revealed the use of the following in South Africa: blogs (46.6%), game downloads (84.3%), Instagram (44.7%), Twitter (47.8%), MXit (39%), and Facebook (86.5%). Despite the differences in the use of social media channels in the two countries, preliminary results showed the increasing importance of social media for communication among their populace.

5.4 MOBILE MONEY ADOPTION

The study aggregated the respective mobile money adoption rates for South Africa and Zimbabwe, which are shown in Figure 5.4 below.

Figure 5.4: Mobile money penetration in South Africa and Zimbabwe



Source: Author’s compilation

The indicative results on mobile money adoption shown in Figure 5.4 above indicate that 1.4% (71) of the South African adult population had adopted mobile money services compared to 49% (1836) in Zimbabwe. In South Africa, mobile money services were offered through money transfers at the supermarkets and or retail outlets (Shoprite's money market or Pep's Capfin) and through cell phone money (eWallet, mPesa, Send-imali, Instantmoney, Cash send, Mobile Money from Pick 'n Pay/Boxer). Zimbabwe had three mobile network operator-led mobile money transfer offerings namely: EcoCash, TeleCash and OneMoney, provided by Econet Wireless Zimbabwe, Telecel Zimbabwe and the state-owned NetOne respectively. The low demand for mobile money services in South Africa was a result of the following: (1) a high bank account saturation, and (2) the existence of well-established highly trusted alternate payment and remittance means, and (3) a strict regulatory framework (FinMark Trust, 2016; FinMark Trust, 2017). Subsequently, the subdued use of mobile money services in South Africa affected viability, resulting in the decommissioning by some services providers such as Vodacom and MTN (Reuters, 2016; Perlman, 2012).

Notwithstanding the current challenges, South Africa does have the necessitating conditions for the adoption of mobile money services (FinMark Trust, 2016). Firstly, the seemingly high proportion of banked adults does, however, mask the underlying issue of the financial access needs of the population at the bottom of the pyramid, who often resort to informal means of transacting. Meyer (2016) reported that South Africa's informal economy is estimated be around 160 billion Rands, with the majority of these transactions being cash based. Secondly, Camner, Pulver and Sjöblom (2009) found that cash is still the primary transacting mechanism in South Africa, but is fraught with constrained affordable credit access, safe storage and transportation risks. The risks and access to credit gaps existing in South Africa could be effectively addressed by the use of mobile money services. Inclusion of the unbanked into formal financial services employing a secure and sustainable mobile money model would be beneficial to individuals and to national socio-economic development, as literature has found (Ehrbeck et al., 2012; Donovan, 2012; International Monetary Fund, 2016).

The key drivers of mobile money use identified in Zimbabwe included: (1) a poor physical bank branch presence in the rural peripheries, (2) stringent know your customer (KYC) requirements paired with high account opening and maintenance fee requirements by banks, which are beyond the reach of many, (3) lack of trust in the banking sector owing to prior systemic failures, (4) the liquidity crunch currently experienced in the country that has resulted in increased demand for alternate payment means, (5) an extensive mobile money agent distribution throughout the country which provides convenient, cost effective means of payments, savings, insurance, credit and remittance services to many who were previously financially excluded, and (6) the permissive regulatory approach of the Reserve Bank of Zimbabwe (RBZ) which encourages financial innovation and inclusion, yet protects customers (RBZ, 2016; FinMark Trust, 2016).

5.4.1 Determinants of mobile money adoption

While not conclusive without rigorous econometric models, the results presented in Table 5.4 and 5.5 below reflect the determinants of mobile money adoption in South Africa and Zimbabwe respectively.

Table 5.4: Determinants of mobile money adoption in South Africa

		Mobile money adoption in South Africa					
		Non-adoption of Mobile Money technology			Mobile Money Adoption		
Determinant variables		N	% of Category	% of Total	N	% of Category	% of Total
Household location	Rural: Traditional & Farms	1111	22.8%	22.5%	8	11.3%	0.2%
	Urban	3759	77.2%	76.1%	63	88.7%	1.3%
Household size	1	995	20.4%	20.1%	25	35.2%	0.5%
	2	1236	25.4%	25.0%	13	18.3%	0.3%
	3	1038	21.3%	21.0%	11	15.5%	0.2%
	4	759	15.6%	15.4%	12	16.9%	0.2%
	5	411	8.4%	8.3%	6	8.5%	0.1%
	6	216	4.4%	4.4%	3	4.2%	0.1%
	7	94	1.9%	1.9%	0	0.0%	0.0%
	8	57	1.2%	1.2%	0	0.0%	0.0%
	9	26	0.5%	0.5%	1	1.4%	0.0%
	10	13	0.3%	0.3%	0	0.0%	0.0%
	11	9	0.2%	0.2%	0	0.0%	0.0%
	12	8	0.2%	0.2%	0	0.0%	0.0%

	13	1	0.0%	0.0%	0	0.0%	0.0%
	14	1	0.0%	0.0%	0	0.0%	0.0%
	15	2	0.0%	0.0%	0	0.0%	0.0%
	17	1	0.0%	0.0%	0	0.0%	0.0%
	19	1	0.0%	0.0%	0	0.0%	0.0%
	21	1	0.0%	0.0%	0	0.0%	0.0%
	24	1	0.0%	0.0%	0	0.0%	0.0%
Gender	Female	2708	55.6%	54.8%	29	40.8%	0.6%
	Male	2162	44.4%	43.8%	42	59.2%	0.9%
Marital status	Other	2213	45.4%	44.8%	32	45.1%	0.6%
	Single	2657	54.6%	53.8%	39	54.9%	0.8%
Educational attainment	Primary & no education	507	10.4%	10.3%	0	0.0%	0.0%
	Secondary & above	4363	89.6%	88.3%	71	100.0%	1.4%
Employment status	Unemployed	2235	45.9%	45.2%	21	29.6%	0.4%
	Employed	2635	54.1%	53.3%	50	70.4%	1.0%
Bank account ownership	No	1513	31.1%	30.6%	10	14.1%	0.2%
	Yes	3357	68.9%	67.9%	61	85.9%	1.2%
Access to information	Household has no access to information.	0	0.0%	0.0%	0	0.0%	0.0%
	Household has access to information.	4870	100.0%	98.6%	71	100.0%	1.4%
Use of social media (cell phones, radios, television sets, cable decoders, newspapers, magazines)	Non-use of Social Media	2696	55.4%	54.6%	14	19.7%	0.3%
	Social Media use	2174	44.6%	44.0%	57	80.3%	1.2%

Source: Author’s compilation

Table 5.5: Determinants of mobile money adoption in Zimbabwe

Determinant variables		Mobile money adoption in Zimbabwe: Non-adoption of Mobile Money technology N	% of Category	% of Total	Mobile Money Adoption N	% of Category	% of Total
Household location	Rural	1500	78.4%	40.0%	979	53.3%	26.1%
	Urban	414	21.6%	11.0%	857	46.7%	22.9%
Household size	1	114	6.0%	3.0%	108	5.9%	2.9%
	2	139	7.3%	3.7%	190	10.3%	5.1%
	3	303	15.8%	8.1%	331	18.0%	8.8%
	4	367	19.2%	9.8%	388	21.1%	10.3%
	5	361	18.9%	9.6%	316	17.2%	8.4%
	6	248	13.0%	6.6%	209	11.4%	5.6%
	7	152	7.9%	4.1%	141	7.7%	3.8%
	8	105	5.5%	2.8%	76	4.1%	2.0%
	9	95	5.0%	2.5%	55	3.0%	1.5%
	10	30	1.6%	0.8%	22	1.2%	0.6%
	11	0	0.0%	0.0%	0	0.0%	0.0%
Gender	Female	1118	58.4%	29.8%	1011	55.1%	27.0%
	Male	796	41.6%	21.2%	825	44.9%	22.0%
Marital status	Other	1666	87.0%	44.4%	1556	84.7%	41.5%
	Single	248	13.0%	6.6%	280	15.3%	7.5%
Educational attainment	Primary & no education	1008	52.7%	26.9%	439	23.9%	11.7%
	Secondary & above	906	47.3%	24.2%	1397	76.1%	37.3%
Employment status	Unemployed	110	5.7%	2.9%	93	5.1%	2.5%
	Employed	1804	94.3%	48.1%	1743	94.9%	46.5%
Bank account ownership	No	1750	91.4%	46.7%	1332	72.5%	35.5%
	Yes	164	8.6%	4.4%	504	27.5%	13.4%
Access to information (cell phones, radios, television sets, cable decoders, newspapers, magazines)	Household has no access to information	199	10.4%	5.3%	0	0.0%	0.0%
	Household has access to information.	1715	89.6%	45.7%	1836	100.0%	49.0%

Source: Author's compilation

The preliminary findings revealed variances between South Africa, and Zimbabwe where in the former, urbanites (88.7%) were more likely to adopt mobile money technology than the rural population (11.3%), consistent with the findings of GSMA (2015), Lwanga and Adong (2016) and Intermedia (2013). In contrast to the empirical literature, however, preliminary findings of the study revealed that in Zimbabwe, adults residing in rural areas (53.3%) were more likely to adopt the financial technology than their urban counterparts. This dissimilarity in the adoption of mobile money technology between the two countries can be attributed to the variations in the spread of the adult populations, as shown by the descriptive statistics in Table 5.1, where South Africa was a highly urbanised country while (77.4%) Zimbabwe had more adults (66.1%) residing in the rural areas than in towns and cities (33.9%). The greater proportion of mobile money adoption reported among the rural population in Zimbabwe is attributable to rural dwellers' considerable dependence on remittances from family and friends who work and live in urban areas and the diaspora (RBZ, 2016; FinMark Trust, 2016).

The preliminary indications of mobile money adoption with respect to household size revealed that South African households with two or more members (68.4%) were more likely to adopt mobile money services than any other household size category, while in Zimbabwe 94.1% of mobile money adopters also emerged from households with two members and above. These indicative results from both countries support empirical findings by Kikulwe et al. (2014) and Murendo et al. (2015a; 2015b) who concluded that households with many members were more likely to have more adopters of mobile money technology.

Gender wise, the males in South Africa (59.2%) were more likely to use mobile money services than females (40.8%), also consistent with literature (Demirgüç-Kunt et al. 2018; Biscaye et al., 2017; FinMark Trust, 2016). In contrast to research findings, indicative results revealed that in Zimbabwe, females (55.1%) were more likely to adopt mobile money than their male counterparts (44.9%). These results can be attributed to: (1) the fact that there were more women than men residing in rural areas, and (2) more male adults from Zimbabwe have emigrated to the diaspora in search of employment, leaving dependents, mostly composed of the female population, in need of a convenient channel for receiving remittances.

In South Africa, the singles (54.9%) were expected to adopt mobile money services than the “other” marital category (married, divorced, separated, and widowed). However, in Zimbabwe preliminary findings showed that adults belonging to the “other” marital category (84.7%) were expected to adopt mobile money than singles (15.3%), possibly because of the urgent need to remit money to their dependants. Individuals in the age range 17 to 40 years in South Africa (63.4%) and 18 to 40 years in Zimbabwe (87.1%) were more likely to adopt the mobile money technology financial technology. The results from both countries therefore substantiate empirical findings by Gamble et al. (2015), Korniotis and Kumar (2011) and Agarwal et al. (2009), who all concluded that a younger population was more likely than the older generation to adopt mobile money technology.

As far as socioeconomic factors were concerned, the preliminary results from Tables 5.4 and 5.5 revealed that individuals with secondary education and above (South Africa, 100% and Zimbabwe, 76.1%) were more likely to use mobile money services than their counterparts with primary or no education (South Africa, 0% and Zimbabwe, 23.9%), consistent with findings by FinMark Trust (2016), Kikulwe et al. (2014) and Chattopadhyay and Dasgupta (2015). The unemployed were found to be less likely to adopt mobile money technology in both South Africa (29.6%) and Zimbabwe (5.1%) as these services also attracted some fees, although these were lower than conventional bank charges. These results are, however, in contrast to those of FinMark Trust (2016), who found that mobile money accounts ownership was more popular among the unemployed than the employed and the retired.

Results with respect to income showed that individuals whose personal monthly income ranged from R500 and R20 000 (80%) in South Africa, and between USD $51 to USD $251 (73.8%) in Zimbabwe (which translates to an equivalent of R765 to R3765 that is USD 51 to USD 251*15 according to Stats SA 2015 year end foreign exchange rate) were more likely to take up mobile money services than any other income category. A further finding was that bank account ownership had very different outcomes for mobile money adoption in the two countries. In South Africa, individuals with bank accounts were more likely (85.9%) to adopt mobile money services than the unbanked (14.1%). However, in Zimbabwe it was the unbanked adults who were more likely than the banked (27.5%) to take up the financial innovation, consistent with the findings by FinMark Trust (2016). The descriptive results from both South Africa and Zimbabwe also indicated that individuals from households with access to information (cell phones, televisions, radios, newspapers, cable decoders, magazines) (100%) would adopt mobile money services, confirming earlier findings by Murendo et al. (2015a; 2015b).

5.5 SOCIAL MEDIA AND MOBILE MONEY ADOPTION

A chi-square test was performed on each country's data set in order to determine the probable link between mobile money adoption and the use of social media. These results are presented in Tables 5.6 and 5.7 respectively below, and a discussion follows.

Table 5.6: Mobile money adoption and social media use in South Africa

Chi-square test for mobile money adoption and social media in South Africa					
	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	35.895[a]	1	0.000		
Continuity Correction[b]	34.470	1	0.000		
Likelihood Ratio	37.478	1	0.000		
Fisher's Exact Test				0.000	0.000
Linear-by-Linear Association	35.888	1	0.000		
N of Valid Cases	4941				
a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 32.06.					
b. Computed only for a 2x2 table					

Source: Author's compilation

The results from the chi-square test in Table 5.6 on the FinScope consumer survey South Africa 2015 dataset indicated a significant relationship between mobile money adoption and the use of social media, where $\chi^2(1, N = 4941) = 35.895, p = 0.000$.

Table 5.7: Mobile money adoption and social media use in Zimbabwe

Chi-square test for mobile money adoption and social media in Zimbabwe					
	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	424.751[a]	1	0.000		
Continuity Correction[b]	423.220	1	0.000		
Likelihood Ratio	442.134	1	0.000		
Fisher's Exact Test				0.000	0.000
Linear-by-Linear Association	424.638	1	0.000		
N of Valid Cases	3750				
a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 479.81.					
b. Computed only for a 2x2 table					

Source: Author's compilation

The descriptive results from the chi-square tests on the FinScope consumer survey Zimbabwe 2014 data set found a significant relationship between mobile money adoption and the use of social media, where: $\chi^2(1, N = 3750) = 424.751, p = 0.000.$

Despite significant differences in terms of social media usage rates and the variety of social media access channels/proxies, preliminary results from both South Africa and Zimbabwe indicate that generally, there is a positive association between the use of social media and mobile money adoption. The preliminary findings suggesting the increasing importance of social media in influencing mobile money technology adoption these two countries were thus consistent with literature which has found a positive link between social media use and financial behaviour (Kavitha and Bhuvaneswari, 2017; IBM Software, 2012; Savio, 2012; Makina, 2017, Siganos et al., 2014).

5.6 CHAPTER SUMMARY

The descriptive analyses discussed in this chapter provided important insights into the use of social media, mobile money adoption and the possible link between them in South Africa and Zimbabwe. The variances of the three comparative categories identified were discussed. The study noted the following: (1) social media use was higher in South Africa (45.2%) than in Zimbabwe (26.1%), (2) South Africa had a wider variety of social media channels in use than Zimbabwe, (3) mobile money adoption was lower in South Africa (1.4%) than in Zimbabwe (46%), and (4) although not rigorous without econometric estimations, preliminary findings suggested a significant relationship between social media usage and the adoption of mobile money technology in both countries, confirming findings from literature on social media use and financial behaviour (Kavitha and Bhuvaneswari, 2017; IBM Software, 2012; Savio, 2012; Siganos et al., 2014). The indicative results also suggested that mobile money adoption has had a transformative effect on the financial landscape in Zimbabwe while being a merely a complementary service in South Africa, owing to the variations in bank account saturation levels in the two countries. Therefore, the availability of mobile money services and higher social media usage alone do not result in higher rates of mobile money adoption as observed in the case of South Africa. Instead, availability of mobile money services must be in response to market demand as is the case in Zimbabwe. The next chapter discusses the testing of the objectives set out in the introductory chapter using the estimation techniques discussed in chapter four. The empirical results are then discussed in line with theory and findings from closely related empirical studies.

CHAPTER 6

ESTIMATION AND EMPIRICAL RESULTS

6.1 INTRODUCTION

The previous chapter provided the descriptive analyses and preliminary findings from the FinScope South Africa 2015 and Zimbabwe 2014 consumer survey data sets. This chapter presents the results obtained from the econometric estimation techniques developed in the methodology chapter. Section 6.2 provides a description of the principal components analysis procedure employed in determining the respective control variables used in the study for each country. Section 6.3 focuses on the binary logistic regression model and the diagnostic tests. Section 6.4 provides the robustness tests for the two countries. Section 6.5 summarises the main estimation results, while section 6.6 concludes the chapter.

6.2 PRINCIPAL COMPONENT ANALYSIS

The study employed the principal component analysis technique (PCA) as a variable-reduction tool for the FinScope consumer survey South Africa 2015 and Zimbabwe 2014 data sets in order to determine the essential control variables for use in the binary logistic and probit model estimations. The principal component analysis maximizes the amount of variance accounted for in the observed variables by a smaller group of variables called components. Principal component analysis procedure is also applied to the control variables in the current study so as to increase the degrees of freedom for the main variable under investigation; the use of social media. The principal component analysis method was considered appropriate for this study because it does not require many statistical assumptions. The only real assumption is the presence of relatedness between the variables as represented by the correlation coefficient. The following steps were followed in undertaking the principal component procedure: (1) generation of the correlation matrix; (2) partition of variance into commonalities; (3) extraction of initial component solution (eigenvalues); and (4) rotation and interpretation. The principal component analyses for Zimbabwe and South Africa are discussed in Sections 6.2.1 and 6.2.2 below respectively.

6.2.1 Principal component analysis Zimbabwe

The principal components analysis procedure undertaken for Zimbabwe is discussed below.

6.2.1.1 Correlation Matrix Zimbabwe

The correlation matrix represents a simple rectangular array of numbers which gives the correlation coefficients between a single variable and every other variable in the study. The correlation matrix for the FinScope Zimbabwe 2014 consumer survey data set is shown in Table 6.1 below.

Table 6.1: Correlation matrix Zimbabwe

Correlation Matrix[a]							
		Household location	Age	Marital status	Educational attainment	Bank account ownership	Gender
Sig. (1-tailed)	Household location		0.000	0.000	0.000	0.015	0.000
	Age	0.000		0.000	0.000	0.000	0.000
	Marital status	0.000	0.000		0.000	0.070	0.000
	Educational attainment	0.000	0.000	0.000		0.000	0.012
	Bank account ownership	0.015	0.000	0.070	0.000		0.000
	Gender	0.000	0.000	0.000	0.012	0.000	

a. Determinant = .525

b. Tested at the 0.05 level of significance

Source: Author's compilation

The determinant of the correlation coefficients was 0.525, and the study concluded that there were no computational problems with the principal component analysis as the determinant should be greater than zero. Therefore, since the determinant was non-zero and the off-diagonal correlations were zero and close to zero, it can be inferred that the model to be used for analysis was good. Next, the sample adequacy was tested using the Kaiser-Meyer-Olkin (KMO) and Bartlett’s tests. The results of these tests are displayed in Table 6.2 below.

Table 6.2: Kaiser-Meyer-Olkin and Bartlett’s Test Zimbabwe

Kaiser-Meyer-Olkin and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.726
Bartlett's Test of Sphericity	Approx. Chi-Square	2414.194
	Df	15
	Sig.	0.000

Source: Author’s compilation

The Kaiser-Meyer-Olkin measures the sampling adequacy, which determines whether the responses given by the sample are adequate or not, and evaluates the correlations and partial correlations to determine if the data are likely to coalesce on components. Kaiser (1974) recommends values between 0.7 and 0.8. Table 6.2 above shows that the Kaiser-Meyer-Olkin measure for Zimbabwe was 0.726. The study therefore accepted that the sample was adequate and that principal component analysis could proceed.

The Bartlett's test evaluates whether or not the correlation matrix is an identity matrix. This is a matrix in which all the diagonal elements are 1 and all off-diagonal elements are close to 0 as (see Table 6.1). Table 6.2 above shows that at the 5% level of significance, the Bartlett’s Test of Sphericity’s p-value was 0.00. This outcome shows that the correlation matrix was not an identity matrix. The off-diagonal values of our correlation matrix were not zeros, thus the matrix was not an identity matrix. Therefore, principal component analysis was valid and considered to be an appropriate technique for further analysis of the data.

Communality is the sum of the squared component loadings and represents the amount of variance in that variable accounted for by all the components. Table 6.3 displays the communalities for Zimbabwe, that is how much of a variable’s variance has been considered for further analysis. In this case, the study considered variables whose value after extraction was greater than 0.5.

Table 6.3: Communalities Zimbabwe

	Initial	Extraction
Household location	1.000	0.591
Age	1.000	0.746
Marital status	1.000	0.636
Educational attainment	1.000	0.572
Bank account ownership	1.000	0.750
Gender	1.000	0.862
Extraction Method: Principal Component Analysis.		

Source: Author's compilation

According to the communalities displayed in Table 6.3 above for Zimbabwe, the following variables had values greater than 0.5: household location (0.591); age (0.746); marital status (0.636); educational attainment (0.572); bank account ownership (0.750) and gender (0.862).

Table 6.4 below shows the components extracted through the principal component analysis procedure and their eigenvalues. The extraction of initial component solution focuses on the initial eigenvalues or extracted sum of squared loadings columns.

Table 6.4: Component total variance explained Zimbabwe

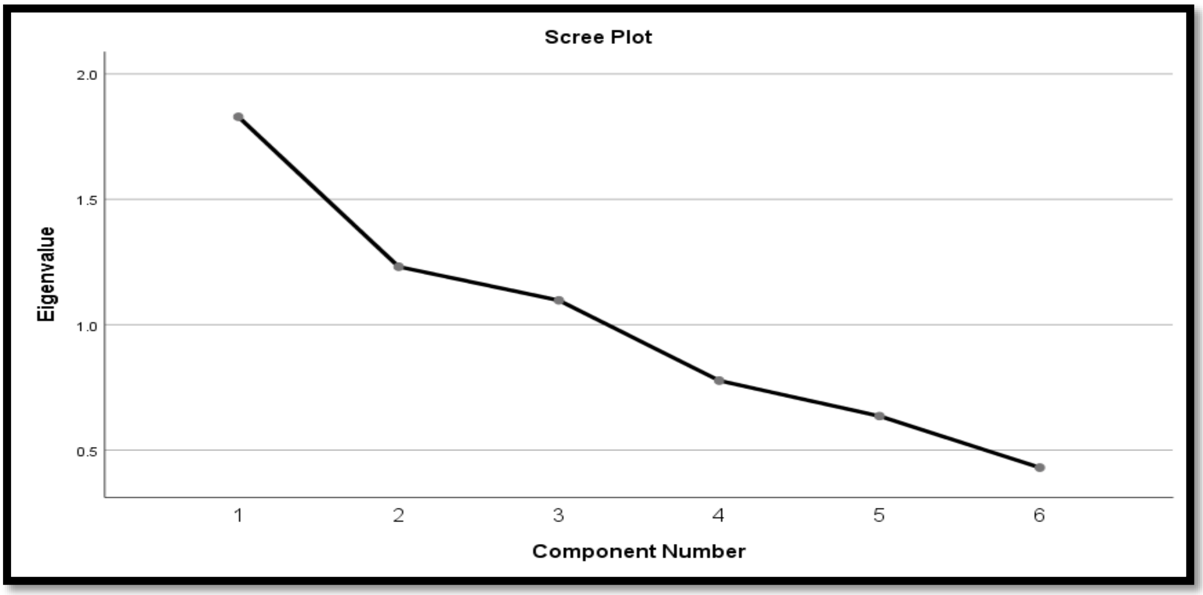
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.829	30.480	30.480	1.829	30.480	30.480	1.655	27.591	27.591
2	1.231	20.520	51.001	1.231	20.520	51.001	1.373	22.881	50.471
3	1.097	18.284	69.285	1.097	18.284	69.285	1.129	18.813	69.285
4	.777	12.950	82.235						
5	.636	10.593	92.828						
6	.430	7.172	100.000						
Extraction Method: Principal Component Analysis.									

Source: Author's compilation

Not all the control variables suggested by the literature and provided in the FinScope consumer survey Zimbabwe 2014 data set were retained. Table 6.4 above shows that only three components whose eigenvalues were greater than 1 were extracted by combining the relevant variables. The first component accounts for the greatest proportion of variance and hence had the highest eigenvalues. The next component explained as much of the left over variance as it could, and the same continued until the last component. In this case, the first three components cumulatively accounted for 69.29% of the total variance. Component 1 explained 30.48% of the total variance, Component 2 accounted for 20.52%, Component 3 explained 18.28% while the remaining three components explained only 30.72%.

A scree plot is a graph of the eigenvalues plotted against all the components and is useful for determining how many components to retain, that is at the point where the curve starts to flatten. Figure 6.1 below shows the scree plot for the Zimbabwean data set, it is clear that the curve begins to flatten after component 3 as each of the subsequent components contributed a smaller proportion of the total variance.

Figure 6.1: Scree plot Zimbabwe



Source: Author’s compilation

The loadings of six variables on the three extracted components for Zimbabwe are shown in Table 6.5 below. The gaps therein represent loadings that were suppressed because they had values which were less than 0.5. A component matrix indicates that Component 1 comprised household location, age, marital status and educational attainment. Component 2 comprised bank account ownership, while Component 3 consisted of marital status and gender.

Table 6.5: Component matrix Zimbabwe

Component Matrix[a]			
	Component		
	1	2	3
Household location	0.575		
Age	-0.755		
Marital status	0.571		0.506
Educational attainment	0.745		
Bank account ownership		0.831	
Gender			0.822
Extraction Method: Principal Component Analysis.			
a. Three components extracted.			

Source: Author's compilation

The component matrix for Zimbabwe in Table 6.5 above shows that the marital status variable appears in both Component 1 and 3, hence there was a need to rectify such an overlap through rotation. The rationale for rotation is thus to reduce the number of components on which the variables under investigation have high loadings. The rotated component matrix for Zimbabwe is shown in in Table 6.6 below and indicates the component loadings for each variable and the component on which each variable is loaded most strongly. The Varimax with Kaiser Normalization method, an orthogonal component rotation method, was employed to maximise the variance of each of the components. This technique is a procedure in which the components involved are extracted so that their axes are maintained at 90 degrees. Each component is independent of, or orthogonal to all other components. The correlation between the components is determined to be zero.

Table 6.6: Rotated component matrix Zimbabwe

Rotated Component Matrix[a]			
	Component		
	1	2	3
Household location		0.696	
Age	-0.832		
Marital status	0.734		
Educational attainment	0.569		
Bank account ownership		0.795	
Gender			0.928
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.			
a. Rotation converged in six iterations.			

Source: Author's compilation

The rotated component matrix loadings in Table 6.6 above illustrate that age (-0.832), marital status (0.734) and educational attainment (0.569) variables loaded strongly on Component 1; household location (0.696) and bank account ownership (0.795) were strongly loaded on Component 2; while gender (0.928) was strongly on Component 3. These high loading value imply that the components had a very strong influence on mobile money adoption in Zimbabwe. Thus, after rotation (Table 6.4 under Rotation of Sum of Squared Loadings and % of variance columns), Component 1 accounted for 27.59% of the variance; Component 2 accounted for 22.88% of the variance; while Component 3 accounted for 18.81% of the variance. Cumulatively, the three extracted components explained 69.285% of the variance in mobile money adoption in Zimbabwe.

The component transformation matrix for Zimbabwe shown in Table 6.7 below shows the correlations among the three components prior to and after rotation. A discussion follows.

Table 6.7: Component transformation matrix Zimbabwe

Component Transformation Matrix			
Component	1	2	3
1	0.854	0.517	-0.064
2	-0.434	0.773	0.463
3	0.289	-0.367	0.884
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.			

Source: Author's compilation

Through the principal components analysis procedure, the study selected five of the six control variables extracted through the principal component procedure. Selection of variables was made based on the highest component loadings (irrespective of the sign) after rotation for use in the main estimation procedure. The chosen control variables used in the main regression estimation for Zimbabwe were: gender (0.928), age (-0.832), bank account ownership (0.795), marital status (0.734) and household location (0.696).

6.2.2 Principal component analysis South Africa

The principal components analysis procedure undertaken for South Africa is discussed below.

6.2.2.1 Correlation Matrix South Africa

The principal components analysis procedure undertaken for South Africa is discussed in this section. Table 6.8 below displays the correlation matrix output for South Africa, with interpretation following.

Table 6.8: Correlation matrix South Africa

Correlation Matrix[a]									
		Household location	Age	gender	Marital status	Personal monthly income	Educational attainment	Employment status	Bank account ownership
Sig. (1-tailed)	Household location		0.014	0.038	0.000	0.000	0.000	0.000	0.000
	Age	0.014		0.000	0.000	0.000	0.000	0.000	0.000
	Gender	0.038	0.000		0.002	0.000	0.000	0.000	0.000
	Marital status	0.000	0.000	0.002		0.000	0.000	0.008	0.000
	Personal monthly income	0.000	0.000	0.000	0.000		0.000	0.000	0.000
	Educational attainment	0.000	0.000	0.000	0.000	0.000		0.000	0.000
	Employment status	0.000	0.000	0.000	0.008	0.000	0.000		0.000
	Bank account ownership	0.000	0.000	0.000	0.000	0.000	0.000	0.000	

a. Determinant = 0.549

b. 5% level of Significance

Source: Author's compilation

The determinant of the correlation matrix for South Africa in Table 6.8 above was 0.549, and the study concluded that there were no computational problems with the principle component analysis. Therefore, since the determinant was non-zero and the off-diagonal correlations were close to zero, it could be inferred that the model to be used for analysis was good, and the sample adequacy was tested using the Kaiser-Meyer-Olkin (KMO) and Bartlett's tests, which are shown in Table 6.9 below.

The Kaiser-Meyer-Olkin measure of sampling adequacy statistic for South Africa shown in Table 6.9 below is large (0.754) and therefore, in accordance with Kaiser (1974), it was accepted that the sample was adequate and that principal component analysis could proceed. The results of Bartlett's Test of Sphericity shown in Table 6.9 below indicated a p-value of 0.00. This result indicated that the Bartlett's Test of Sphericity for South Africa was significant at 0.05 level, and it could be concluded that the correlation matrix was not an identity matrix. Therefore, the principal component analysis was valid and regarded as an appropriate technique for further analysis of the data.

Table 6.9: Kaiser-Meyer-Olkin and Bartlett's Test South Africa

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.754
Bartlett's Test of Sphericity	Approx. Chi-Square	5980.366
	Df	28
	Sig.	0.000

Source: Author's compilation

Table 6.10 below displays the communalities for South Africa, that is how much of each variable's variance has been considered for further analysis. In this case, the study considered variables whose value after extraction was greater than 0.5.

Table 6.10: Communalities South Africa

	Initial	Extraction
Household location	1.000	0.539
Age	1.000	0.743
Gender	1.000	0.656
Marital status	1.000	0.679
Personal monthly income	1.000	0.608
Educational attainment	1.000	0.543
Employment status	1.000	0.623
Bank account ownership	1.000	0.519
Extraction Method: Principal Component Analysis.		

Source: Author's compilation

The communalities for South Africa reflected in Table 6.10 above show that the following variables had values greater than 0.5 after extraction: household location (0.539); age (0.743); gender (0.656); marital status (0.679); personal monthly income (0.608); educational attainment (0.543); employment status (0.623); and bank account ownership (0.519).

The components extracted from the principal component analysis technique for South Africa are displayed in Table 6.11 below and discussed thereafter.

Table 6.11: Component total variance explained South Africa

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.175	27.183	27.183	2.175	27.183	27.183	2.126	26.572	26.572
2	1.692	21.146	48.329	1.692	21.146	48.329	1.696	21.202	47.773
3	1.043	13.044	61.372	1.043	13.044	61.372	1.088	13.599	61.372
4	.846	10.572	71.945						
5	.707	8.843	80.787						
6	.621	7.761	88.548						
7	.490	6.127	94.674						
8	.426	5.326	100.000						

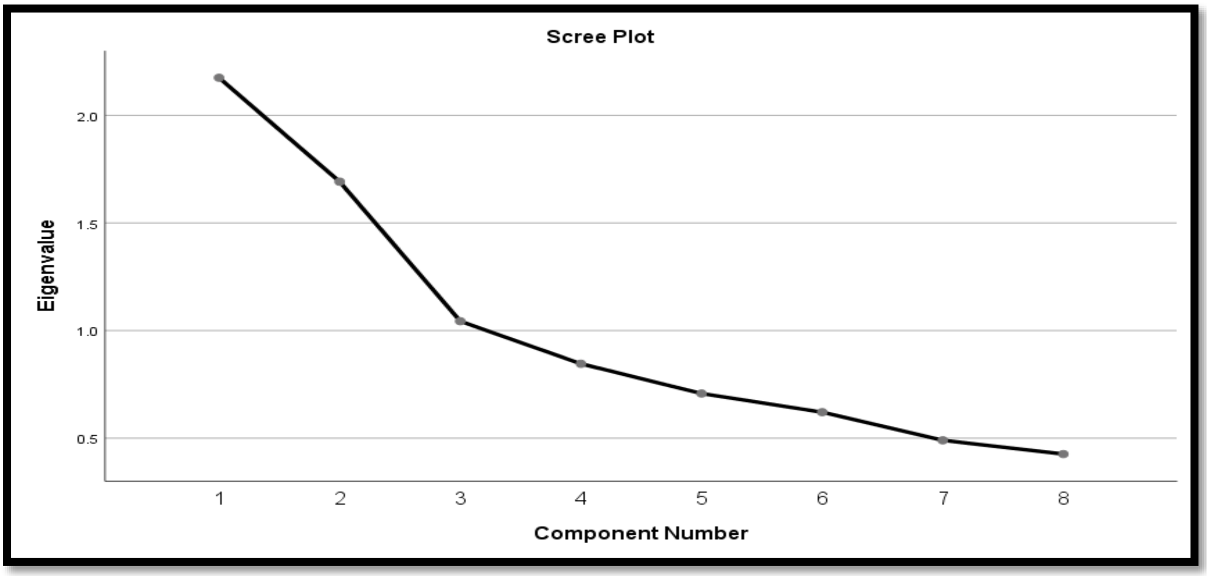
Extraction Method: Principal Component Analysis.

Source: Author's compilation

The initial eigenvalues or extracted sum of squared loadings columns were used for analysis and interpretation. Not all the control variables suggested by the literature and made available in the FinScope consumer survey South Africa 2015 data set were retained. Table 6.11 above shows that three from a total of eight components had eigenvalues greater than 1, and these were therefore extracted by combining the relevant variables. The first three components cumulatively accounted for 61.37% of the total variance. Component 1 accounted for 27.18% of the variation, Component 2 accounted for 21.15%, Component 3 explained 13.04% while the remaining five components explained only 38.628% of the total variance.

Figure 6.2 below shows the scree plot for the FinScope South Africa 2015 data set; it is clear from the graph that after Component 3 there is a sharp change in the curvature of the scree plot. This indicates that after Component 3 the total variance accumulated in smaller proportions for each subsequent component.

Figure 6.2: Scree plot South Africa



Source: Author’s compilation

Table 6.5 below shows the loadings of eight variables (irrespective of the sign) on the three extracted components for South Africa. The gaps represent loadings that were suppressed because their values which were less than 0.5.

Table 6.12: Component matrix South Africa

Component Matrix[a]			
	Component		
	1	2	3
Household location	0.501		-0.532
Age		-0.851	
Gender			0.736
Marital status		0.763	
Personal monthly income	0.772		
Educational attainment		0.522	
Employment status	0.713		
Bank account ownership	0.717		

Extraction Method: Principal Component Analysis.

a. Three components extracted.

Source: Author’s compilation

The component matrix in Table 6.12 above indicates that Component 1 consisted of household location, personal monthly income, employment status and bank account ownership; Component 2 contained age, marital status and educational attainment; while Component 3 comprised household location and gender. The component matrix for South Africa shows that the household location variable appeared in both Components 1 and 3, such an overlap thus had to be rectified using the Varimax with Kaiser Normalization rotation technique. The rotated component matrix for South Africa is shown in Table 6.13 below and illustrates the component loadings for each variable and the component on which each variable was loaded most strongly.

Table 6.13: Rotated component matrix South Africa

Rotated Component Matrix[a]			
	Component		
	1	2	3
Household location			.617
Age		-.861	
Gender			-.685
Marital status		.792	
Personal monthly income	.763		
Educational attainment			
Employment status	.771		
Bank account ownership	.684		
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.			
a. Rotation converged in eight iterations.			

Source: Author's compilation

Based on the rotated component matrix loadings reflected in Table 6.13, personal monthly income (0.763), employment status (0.771) and bank account ownership (0.684) were strongly loaded on Component 1; age (-0.861) and marital status (0.792) were heavily loaded on Component 2; household location (0.617) and gender (-0.685) were strongly loaded on Component 3. The high loading values implied that the component had a very strong influence on mobile money adoption in South Africa. Following rotation, the educational attainment variable was not loaded onto any component. Consequently, following rotation (refer to Table 6.11 under the Rotation Sums of Squared Loadings column), Component 1 accounted for 26.57% of the variance, Component 2 explained 21.20% of the variance, while Component 3 accounted for 13.04%. Cumulatively, these three components explained 61.37% of the total variance in mobile money technology adoption in South Africa.

Table 6.14 below displays the component transformation matrix for South Africa, reflecting the correlations among the three components prior to and after rotation.

Table 6.14: Component transformation matrix South Africa

Component	1	2	3
1	.973	-.118	.197
2	.127	.991	-.035
3	.191	-.059	-.980
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.			

Source: Author’s compilation

The study selected 5 out of 7 control variables from the principal components analysis procedure. Selection was based on the highest component loadings (irrespective of the sign) after rotation using the Varimax with Kaiser Normalization method. The chosen control variables for South Africa that were used in the main regression estimation were: age (-0.861); marital status (0.792); employment status (0.771); personal monthly income (0.763); gender (-0.685).

6.3 BINARY LOGISTIC REGRESSION MODELS

In this section, the study presents the logistic regression models that predicted mobile money adoption in South Africa and Zimbabwe. Table 6.15 below provides the original coding of the dependent variable (mobile money adoption) in the two countries, where 0 denotes non-adoption of mobile money technology, and 1 denotes adoption.

Table 6.15: Dependent variable coding

Dependent Variable Encoding	
Original Value	Internal Value
Non-adoption of Mobile Money technology	0
Mobile Money Adoption	1

Source: Author's compilation

6.3.1 Zimbabwe

The study modelled the likelihood of mobile money adoption by an adult in Zimbabwe as a function of the use of social media (independent variable), the interaction term (mobile money adoption × use of social media), and control variables (gender, age, bank account ownership, marital status and household location). Three binary logistic regression outputs obtained using the Enter method in IBM SPSS 25 are presented: Model 1, Model 2, and Model 3. These are discussed below.

6.3.1.1 Model 1

This model consists of the independent variable (use of social media) and is presented in two forms: Block 0, and Block 1. The Block 0 is a null model - that is one which only consists of the intercept, which in IBM SPSS is referred to as the constant. Table 6.16 below displays the Model 1 Block 0 output which consists of the classification table, variables in the equation and variables not in the equation.

Table 6.16: Zimbabwe Model 1 Block 0

Classification Table[a,b]

Observed			Predicted: Mobile money adoption: Non-adoption of Mobile Money technology	Predicted: Mobile money adoption: Mobile Money Adoption	Predicted: Percentage Correct
Step 0	Mobile money adoption	Non-adoption of Mobile Money technology	1914	0	100.0
		Mobile Money Adoption	1836	0	.0
	Overall Percentage				51.0

a . Constant is included in the model.

b. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	Df	Sig.	Exp(B)
Step 0	Constant	-.342	.0115	10.692	1	.001	.710

Variables not in the Equation

			Score	Df	Sig.
Step 0	Variables	Use of social media	424.751	1	.000
	Overall Statistics		424.751	1	.000

Source: Author’s compilation

The classification table shown in Table 6.16 above indicates how well the null model predicted mobile money adoption in Zimbabwe. Given the base rates of the two decision options of adoption or non-adoption, (1836/3750 = 49% chose to adopt mobile money adoption while 51% did not), and with no other information, the best strategy was to predict, for every case, that an individual would choose to adopt mobile money. Using that strategy, the model would be correct 51% of the time. Thus, the overall percent of cases that were correctly predicted by the null was 51%, and it could be concluded that the model was valid, and therefore a good fit for the data which could be replicated.

In Table 6.16 above, the intercept-only model is displayed under the Variables in the Equation section. The Wald Chi-square tests the null hypothesis that the constant equals zero. This hypothesis was rejected because Table 6.16 above shows that the p-value (0.001) was less than the critical value of 0.05. Therefore, the study concluded that the constant was not zero and the predicted odds of mobile money adoption for Zimbabwe in Model 1 Block 0 were 0.710. The Score test under the Variables not in the Equation section in Table 6.16 above was used to predict whether or not the independent variable would be significant in the model. Considering the p-values, the use of social media variable (0.000) was statistically significant at 5%. The overall statistics p-value of 0.000 shows the result of adding the use of social media (independent variable) to the null model, and in this case, it was statistically significant at 5% level.

The Model 1 Block 1 shows the results of the binary logistic regression model following the addition of the selected independent variable – use of social media, and these are displayed in Table 6.17 below.

Table 6.17: Zimbabwe Model 1 Block 1

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	442.134	1	.000
	Block	442.134	1	.000
	Model	442.134	1	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	4754.847[a]	.111	.168

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	Df	Sig.
1	.000	0	.

Classification Table[a]

Observed			Predicted: Mobile money adoption: Non-adoption of Mobile Money technology	Predicted: Mobile money adoption: Mobile Money Adoption	Predicted: Percentage Correct
Step 1	Mobile money adoption	Non-adoption of Mobile Money technology	1691	223	88.3
		Mobile Money Adoption	1079	757	41.2
	Overall Percentage				65.3

a. The cut value is .500

Table 6.17 continued

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Use of social media	1.671	.386	81.491	1	.000	5.317
	Constant	-.449	.039	13.963	1	.000	.638

a. Variable(s) entered on step 1: Use of social media.

Source: Author's compilation

The Omnibus tests of model coefficients give the result of the likelihood ratio test which indicates whether the addition of the independent variable (use of social media) contributes significantly to an improvement in the model fit. As indicated in Table 6.17 above, the Omnibus tests of model coefficients provided a Chi-Square of

442.134 on 1 df, a p-value of the block (use of social media) of 0.000 which was less than the 0.05 significance level. This means that the Model 1 Block 1 was a significant improvement from Model 1 Block 0, with the use of social media positively and significantly influencing mobile money adoption in Zimbabwe. The block and step p-values were equal to the model value since all variables (constant and independent) were entered at the same time.

The model summary provided in Table 6.17 above indicates that the addition of the use of social media variable to the null model reduced the -2 Log likelihood statistic to 4754.847 from 5196.981 (4754.847 + 442.134 in the Omnibus tests of model coefficients) in the null model. Thus, a reduction of the -2 log likelihood statistic reflects an improvement in the model fit following the addition of the independent variable. In standard regression, the coefficient of regression R^2 value gives an indication of how much variation in the dependent variable is explained by the model. The study notes that the coefficient of regression R^2 cannot be calculated for binary logistic regression. However, the model summary in Table 6.17 provides the values of two pseudo R^2 which try to measure something similar. The pseudo R^2 values are thus approximations and should not be overly emphasised. This study used the Nagelkerke R^2. According to Model 1 Block 1 in Table 6.17 above, the Nagelkerke R^2 of the independent variable (use of social media) accounted for 16.8% of the variance in mobile money technology adoption decision in Zimbabwe. This value is low, implying a poor fit of the model; 83.2% of the variance in mobile money technology adoption decision was accounted for by other variables not included in Model 1 Block 1.

At a 95% confidence level, the Hosmer and Lemeshow test (see Table 6.17) reflected no statistical significance owing to the inclusion of only the social media in Model 1 Block 1, necessitating further blocks of the binary logistic regression estimation. Table 6.17 above shows the false positive and false negative error rates in classification, where a false positive would predict that a non-adopter individual would decide to use mobile money technology, when in fact they would not. As reflected in Table 6.17, the decision rule predicted a decision of mobile money technology adoption 980 times; the prediction was wrong 223 times. Therefore, there was a false positive of 22.8% (223/980). A false negative would predict that an individual would decide not to adopt mobile money technology, when in fact they would do so. The decision rule predicted the non-adoption of mobile money technology 2770 times. That prediction was wrong 1079 times, a false negative rate of 39% (1079/2770). The overall model correct classification for Model 1 Block 1 was 65.3%. Thus, Model 1 Block 1 was an improvement in the model fit compared to the null model.

As indicated in the Variables in the Equation section in Table 6.17, the B-values are the log-odds for the binary logistic regression equation for predicting mobile money adoption in Zimbabwe based on the use of social media. These estimates show the extent of the relationship between mobile money adoption and the use of social media, where the mobile money adoption variable is on the logistic scale. In terms of the Wald test, the coefficient of social media was statistically significant at the 95% confidence level, meaning that the independent variable was a significant predictor of mobile money technology adoption decision in Zimbabwe. The study concluded that use of social media variable had a positive (B = 1.671) and statistically significant effect (p-value =0.000) on mobile money adoption in Zimbabwe. Therefore, for every one-unit increase in the use of social media, a 5.317 increase in the log-odds of mobile money adoption was expected. The fitted Model 1 Block 1 equation is shown below:

$$\text{Mobile money adoption} = -0.449 + 1.671 \times \text{Use of social media} \tag{10}$$

6.3.1.2 Model 2

The second model involved the addition of use of social media and the interaction term (mobile money adoption × use of social media). The interaction term captured how the overall mobile money adoption would be increased by the simultaneous adoption of mobile money technology and use of social media effect, that is, an individual simultaneously used technology and social media. Similar to Model 1, Model 2 is presented as Block 0 and Block 1. Model 2 Block 0 is the null model, the output of which is shown in Table 6.18 below.

Table 6.18: Zimbabwe Model 2 Block 0

Classification Table[a,b]

Observed			Predicted: Mobile money adoption: Non-adoption of Mobile Money technology	Predicted: Mobile money adoption: Mobile Money Adoption	Predicted: Percentage Correct
Step 0	Mobile money adoption	Non-adoption of Mobile Money technology	1914	0	100.0
		Mobile Money Adoption	1836	0	.0
	Overall Percentage				51.0

a. Constant is included in the model.

b. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-.342	.115	10.692	1	.001	.710

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	Mobile money adoption × Use of social media	2954.264	1	.000
		Use of social media	424.751	1	.000
	Overall Statistics		3060.677	2	.000

Source: Author's compilation

Given the base rates of the two decision options (1836/3750 = 49% chose to adopt mobile money adoption and 51% did not) (see Table 6.18) and with no other information, the best strategy was to predict, for every case, that an individual would choose to adopt mobile money. Using this strategy, the model would be correct 51% of the time. Thus, overall percent of cases that were correctly predicted by the null was 51%, and it could be concluded that the model was a good fit for the data and could be replicated. The intercept-only model is displayed under the "Variables in the Equation" section. The Wald Chi-square tests the null hypothesis that the constant equals zero. This hypothesis was rejected because the p-value (0.001) was less than the critical value of 0.05. Therefore, the study concluded that the constant was not zero and the predicted odds of mobile money adoption for Zimbabwe in Model 2 Block 0 were 0.710. Looking at the p-values from the Score test under the Variables not in the Equation section in Table 6.18, mobile money adoption × use of social media (0.000) and use of social media (0.000) were statistically significant at a 95% confidence level. The overall statistics p-value of 0.000 indicated that the result of including the interaction term in the model, it was significant at the 5% level.

Model 2 Block 1 (see Table 6.19 below) displays the outcome of the binary logistic regression model consisting of the use of social media and mobile money adoption × use of social media (interaction term). A discussion of the results follows.

Table 6.19: Zimbabwe Model 2 Block 1

Omnibus Tests of Model Coefficients

		Chi-square	Df	Sig.
Step 1	Step	1493.283	2	.000
	Block	1493.283	2	.000
	Model	1493.283	2	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	3703.699[a]	.669	.892

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	Df	Sig.
1	.000	1	.902

Classification Table[a]

Observed			Predicted: Mobile money adoption: Non-adoption of Mobile Money technology	Predicted: Mobile money adoption: Mobile Money Adoption	Predicted: Percentage Correct
Step 1	Mobile money adoption	Non-adoption of Mobile Money technology	1691	223	88.3
		Mobile Money Adoption	0	1836	100
	Overall Percentage				94.1

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Mobile money adoption × Use of social media	2.279	.614	30.931	1	.002	9.767
	Use of social media	1.217	.245	24.757	1	.000	3.377
	Constant	-.482	.1264	14.626	1	.000	.618

a. Variable(s) entered on step 1: Mobile money adoption × Use of social media, Use of social media.

Source: Author's compilation

The Omnibus tests of model coefficients gave a Chi-Square of 1493.283 on df 2, and the p-value of the block (mobile money adoption × use of social media; use of social media) was 0.000, and therefore statistically significant at the 95% confidence level. Thus, Model 2 Block 1 model was a significant improvement on Model 2 Block 0 - the addition of the social media and the interaction term to the intercept-only model significantly and positively influenced mobile money technology adoption in Zimbabwe. The block and step p-values were equal to the model's value since all variables (interaction term, use of social media and the constant) were entered at the same time.

The model summary in Table 6.19 further illustrates that the addition of the interaction term to the null model results in a decrease in the -2 Log likelihood statistic to 3703.699 from 5196.981 (3703.699 + 1493.283 from the Chi-square in the Omnibus tests of model coefficients) in the null model. This reduction of the -2 Log likelihood statistic implies an improvement in model fit after the inclusion of the interaction term. Considering the pseudo R^2, the Nagelkerke R^2 reveals that the interaction term (mobile money adoption × use of social media) and the use of social media accounted for 89.2% of the total amount of variance in the mobile money technology adoption decision. Only 10.8% of the variance in mobile money adoption was explained by other variables which were excluded from Model 2 Block 1, and therefore the Nagelkerke R^2 value indicated a good fit of the model in explaining mobile money technology adoption in Zimbabwe.

At a 95% confidence level, the Hosmer-Lemeshow test was not statistically significant (p-value = 0.902) however. This insignificance indicated that the binary logistic regression was an adequate fit to the data since a good fit model has a p-value that is greater than the 0.05 significance level (Hosmer and Lemeshow, 2000). The classification of the false positive and false negative error rates displayed in Table 6.19 indicates that the decision rule predicted a decision of mobile money technology adoption 2059 times; the prediction was wrong 223 times. Therefore, there was a false positive of 10.83% (223/2059). The decision rule predicted the non-adoption of mobile money 1691 times, and that prediction was correct for a false negative of 0% (0/1691). The overall model correct classification was 94.1%. Thus, Model 2 Block 1 showed an improvement in the model fit following the addition of social media and the interaction term to the null model (Model 2 Block 1).

In terms of the Wald test from the Variables in the Equation, Table 6.19 shows that the coefficients of the mobile money adoption × use of social media and use of social media variables were statistically significant at the 95% confidence level. Thus, it was concluded that the interaction term (B = 2.279 and p-value of 0.002) and social media (B = 1.217 and p-value of 0.000) had a positive and statistically significant effect on mobile money adoption decision in Zimbabwe. Therefore, for every one-unit increase in the interaction term, a 9.767 increase in the log-odds of overall mobile adoption was expected, holding the use of social media constant. Also, for every one-unit increase in the use of social media, a 3.377 increase in the log-odds of mobile money adoption was expected, holding the interaction term constant. The fitted Model 2 Block 1 equation is shown below:

Mobile money adoption = -0.482 + 2.279 × Interaction term (mobile money adoption × use of social media) + 1.217 × Use of social media
(11)

6.3.1.3 Model 3

The third model is the full model, comprising the use of social media, the interaction term and five control variables determined from the principal components analysis procedure for Zimbabwe. As in the earlier models, Model 3 has two components- Block 0 and Block 1. The binary logistic regression output for Model 3 Block 0 is displayed in Table 6.20 below and explained thereafter.

Table 6.20: Zimbabwe Model 3 Block 0

Classification Table[a,b]					
Observed			Predicted		
			Mobile money adoption		Percentage Correct
			Non-adoption of Mobile Money technology	Mobile Money Adoption	
Step 0	Mobile money adoption	Non-adoption of Mobile Money technology	1914	0	100.0
		Mobile Money Adoption	1836	0	51.0
	Overall Percentage				51.0

a. Constant is included in the model.

b. The cut value is .500

Variables in the Equation							
		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-.342	.115	10.692	1	.001	.710

Variables not in the Equation					
			Score	df	Sig.
Step 0	Variables	Use of social media	424.751	1	.000
		Mobile money adoption × Use of social media	2988.757	1	.000
		Gender	4.276	1	.039
		Age	36.705	1	.000
		Bank account ownership	228.222	1	.000
		Marital status	4.074	1	.044
		Household location	262.392	1	.000
	Overall Statistics		3074.773	7	.000

Source: Author's compilation

The classification table in Table 6.20 shows that given the base rates of the two decision options (1836/3750 = 49% chose to adopt mobile money adoption and 51% did not), and with no other information, the best strategy was to predict, for every case, that an individual would choose to adopt mobile money. Using that strategy, the model would be correct 51% of the time. Thus, the overall percent of cases that were correctly predicted by the null was 51%, and it could be concluded that the model was valid, a good fit for the data and replicable. From the Variables in the

Equation section in Table 6.20 above, it is evident that in the Wald test the null hypothesis (that the constant equals zero) was rejected because the p-value (0.001) was less than the critical value of 0.05. Therefore, it was concluded that the constant was not zero and the predicted odds of mobile money adoption for Zimbabwe in Model 3 Block 0 were 0.710. The Score test displayed under the Variables not in the Equation section in Table 6.20 above was used to predict whether or not the control variable would be significant in the model. Taking into consideration the p-values, in addition to the use of social media and the interaction term, all the selected control variables were statistically significant at 5%. The overall statistics' p-value of 0.000 indicates that the addition of all variables (use of social media, mobile money adoption × use of social media, gender, age, bank account ownership, marital status and household location) to the null model led to an improvement in the model fit because such an inclusion was statistically significant at 5%.

The output of Model 3 Block 1 binary logistic regression is displayed below in Table 6.21. The results are discussed below.

Table 6.21: Zimbabwe Model 3 Block 1

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	1640.974	7	.000
	Block	1640.974	7	.000
	Model	1640.974	7	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	3556.008[a]	.673	.898

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	Df	Sig.
1	6.059	8	.641

Classification Table[a]

Observed			Predicted: Mobile money adoption: Non-adoption of Mobile Money technology	Predicted: Mobile money adoption: Mobile Money Adoption	Predicted: Percentage Correct
Step 1	Mobile money adoption	Non-adoption of Mobile Money technology	1691	223	88.3
		Mobile Money Adoption	0	1836	100.0
	Overall Percentage				94.1

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	Df	Sig.	Exp(B)
Step 1[a]	Mobile money adoption × Use of social media	1.655	.269	20.586	1	.000	5.233
	Use of social media	1.030	.241	16.346	1	.001	2.801
	Gender	-.479	.161	.461	1	.000	.619
	Age	.-352	.003	1.751	1	.631	.703
	Bank acc. ownership	-.297	4.133	6.436	1	.002	.743
	Marital status	-.207	.661	.098	1	.755	.813
	Household location	-.537	.145	8.752	1	.000	.584
	Constant	-.519	.176	9.371	1	.000	.595

a. Variable(s) entered on step 1: Mobile money adoption × Use of social media, Use of social media, Gender, Age, Bank account ownership, Marital status, Household location.

Source: Author's compilation

The Omnibus tests of model coefficients in Table 6.21 above produced a Chi-Square of 1640.974 on 7 df, and the p-value of the block (full model after the addition of control variables) was 0.000 and therefore statistically significant at the 95% confidence level. Therefore, according to the Omnibus tests of model coefficients chi-square statistic, Model 3 Block 1 was a significant improvement on Model 3 Block 0 as all variables considered in Model 3 Block 1 were significant determinants of mobile money adoption in Zimbabwe. The block and step p-values were equal to the model value since all variables were entered at the same time.

The model summary in Table 6.21 indicates that the addition of the control variables to the null model resulted in a decrease in the -2 Log likelihood statistic to 3556.008, from 5196.981 (3556.008 + 1640.974 from the Chi-square in the Omnibus tests of model coefficients) in the null model. Consequently, a reduction in the -2 Log likelihood statistic implied an improvement in the Block 1 model fit after the inclusion of the control variables. The Nagelkerke R^2 statistic showed that a model consisting of gender, age, bank account ownership, marital status and household location as control variables accounted for 89.8% of the total amount of variance in the mobile money technology adoption decision. The Nagelkerke R^2 value indicates a good fit of the model because only 10.2% of the variance in mobile money adoption is explained by other variables which were excluded from Model 3 Block 1.

At a 95% confidence level, the Hosmer-Lemeshow test was not statistically significant (p-value = 0.995), however. As in Hosmer and Lemeshow (2000), the result implied that the binary logistic regression in Model 3 Block 1 was an adequate fit to the data because it had a p-value that was greater than the 0.05 significance level. The classification of the false positive and false negative error rates displayed in Table 6.21 above shows that the decision rule predicted a decision to adopt mobile money technology adoption 2059 times, and the prediction was wrong 223 times. Therefore, there is a false positive of 10.83% (223/2059). The decision rule predicted the non-adoption of mobile money 1691 times, and that prediction was correct, making a false negative of 0% (0/1691), with an overall model correct classification of 94.1%.

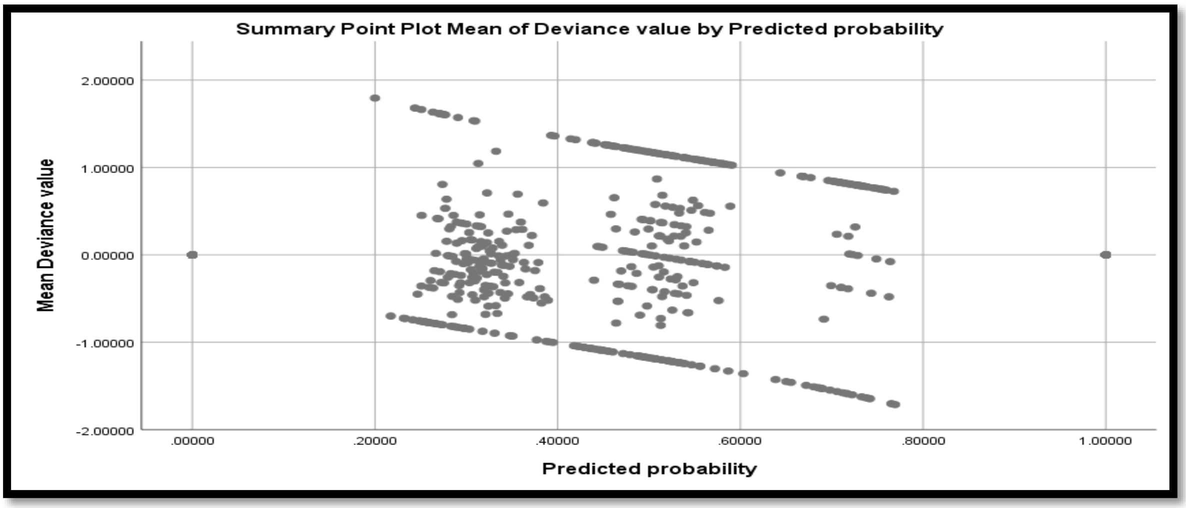
The Wald test in the Variables in the Equation section of Table 6.21 indicates that age and marital status were not significantly different from 0 since their p-values were greater than the 5% and 10% significance levels. The dominant variables are mobile money adoption × use of social media (interaction term), use of social media, gender, bank account ownership and household location. The coefficients of these variables were all statistically significant at the 95% confidence level, meaning that they were significant predictors of mobile money technology adoption in Zimbabwe. Thus, for every unit increase in the interaction term (B =1.655), a 5.233 increase in the log-odds of mobile money adoption was expected, holding all other explanatory variables constant. Also, for every unit increase in the use of social media (B= 1.030), a 2.801 increase in the log-odds of mobile money adoption was expected, holding all other explanatory variables constant. The significant control variables indicated that according to gender (B = -0.479), males had a lower likelihood of mobile money adoption, that is a unit increase in males would reduce the log-odds of mobile money adoption by 0.619, holding all other explanatory variables constant. Bank account ownership (B = -0.297) lowered the likelihood of mobile money adoption, that is a unit increase in bank account ownership translated to a log-odds decrease in mobile money adoption of 0.743, holding all other explanatory variables constant. Household location (B = -0.537) indicated that urbanites had a lower likelihood of mobile money adoption, where a unit increase in urbanites led to a decrease in mobile money adoption of 0.584. Thus, the fitted Model 3 Block 1 equation is as follows:

$$\text{Mobile money adoption} = -0.519 + 1.030 \times \text{Use of social media} + 1.655 \text{ Mobile money adoption} \times \text{Use of social media} - 0.479 \times \text{Gender} - 0.352 \times \text{Age} - 0.297 \times \text{Bank account ownership} - 0.207 \times \text{Marital status} - 0.537 \times \text{Household location} \tag{12}$$

6.3.1.4 Zimbabwe full model diagnosis - deviance

A plot of the mean deviance residuals against the probability illustrating how the full model (Model 3 Block 1) fitted the data is shown in Figure 6.3 below. The model is good if and only if the plotted values are between -3 and 3 (Mekonnen, 2011), and in this instance, the plotted values lie between -2 and 2. Therefore, the binary logistic model for Zimbabwe in Model 3 Block 1 was a good fit for the data.

Figure 6.3: Zimbabwe model fit by deviance

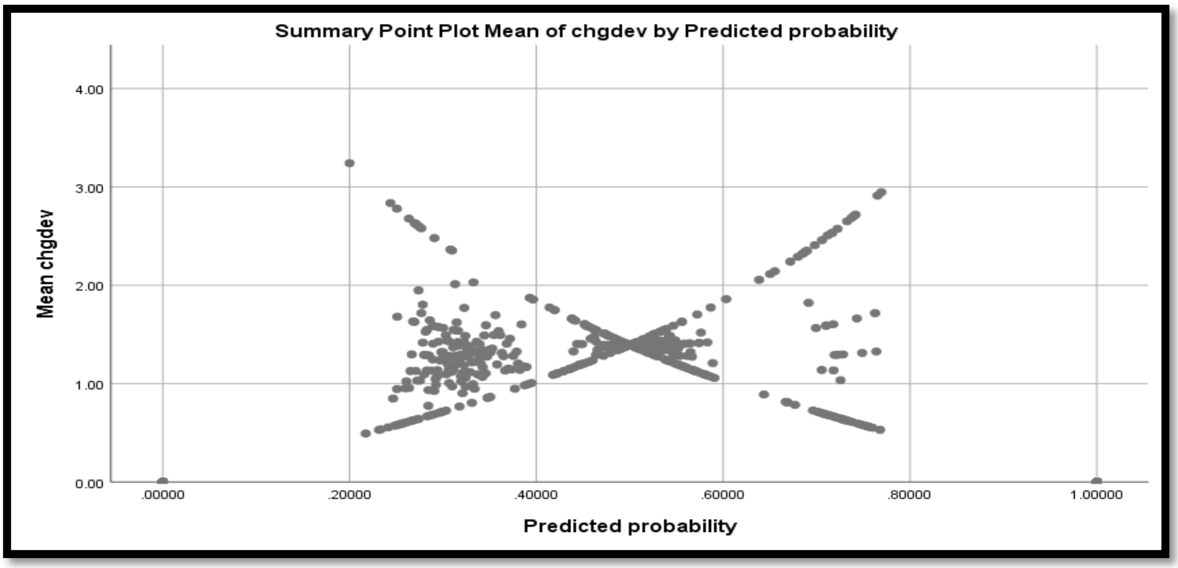


Source: Author’s compilation

6.3.1.5 Zimbabwe full model diagnosis - model predicted probabilities

Further analysis of the model fit to the data was performed by plotting the mean deviance against the predicted probability of mobile money adoption or otherwise. The resultant model fit for Zimbabwe is illustrated in Figure 6.4 below and interpreted thereafter.

Figure 6.4: Zimbabwe model fit predicted probabilities



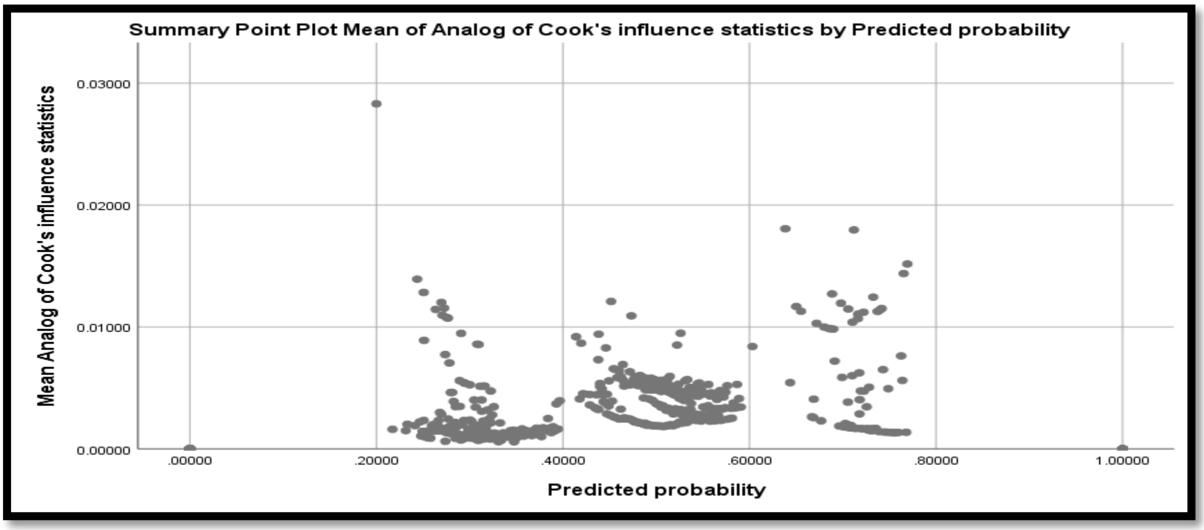
Source: Author’s compilation

The curve that extends from the lower left to the upper right corresponds to cases in which the dependent variable had a value of 0. Thus, the non-adoption of mobile money technology decision was moderately fit by the model. The curve that extends from the upper left to the lower right corresponds to cases in which the dependent variable had a value of 1. Therefore, the adopters who had small model-predicted probabilities of mobile money technology were moderately fit by the model.

6.3.1.6 Zimbabwe full model diagnosis - Cook's distance

The Cook's distance is useful for spotting cases that influence the binary logistic model unduly; observations with a Cook's distance greater than 1 are considered to be influential outliers (Mekonnen, 2011). A summary point plot showing the fit of the model by a measure of the Cook's influence statistics against the predicted probability for Zimbabwe is illustrated in Figure 6.5 below.

Figure 6.5: Zimbabwe model fit by Cook's distance



Source: Author's compilation

If the mean analog of the Cook's influence is below 1, then the model accurately fits the data; in this study it was between 0 and 0.03, and therefore it was concluded that the full binary logistic model (Model 3 Block 1) was a good fit for the data.

6.3.2 South Africa

The study modelled the likelihood of mobile money technology adoption by an adult in South Africa as a function of the use of social media (independent variable), the interaction term (mobile money adoption × use of social media), and five identified control variables (age, marital status, employment status, personal monthly income and gender location). Three binary logistic regression outputs were obtained employing the Enter method in IBM SPSS 25 - Model 1, Model 2 and Model 3.

6.3.2.1 Model 1

The first model consists of the independent variable (use of social media), and is presented in two forms: Block 0, and Block 1. The Block 0 is a null model that consists only of the intercept, which in IBM SPSS is referred to as the constant. The Model 1 Block 0 is shown in Table 6.22 below and explained thereafter.

Table 6.22: South Africa Model 1 Block 0

Classification Table[a,b]

Observed			Predicted: Mobile money adoption: Non-adoption of Mobile Money technology	Predicted: Mobile money adoption: Mobile Money Adoption	Predicted: Percentage Correct
Step 0	Mobile money adoption	Non-adoption of Mobile Money technology	4870	0	100.0
		Mobile Money Adoption	71	0	.0
	Overall Percentage				98.6

a. Constant is included in the model. b. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-.236	.183	11.391	1	.000	.790

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	Use of social media	35.895	1	.000
	Overall Statistics		35.895	1	.000

Source: Author’s compilation

The classification table in Table 6.22 shows how accurately the null model predicted mobile money adoption in South Africa. Given the base rates of the two decision options (71/4941 = 1.44% chose to adopt mobile money adoption and 98.6% did not), and with no other information, the best strategy was to predict, for every case, that an individual would choose to adopt mobile money. Using that strategy, the model would be correct 98.6% of the time. Thus, the overall percent of cases that were correctly predicted by the null was 98.6%, and it can be concluded that the model was valid, a good fit for the data and replicable. The intercept-only binary logistic regression model is displayed under the Variables in the Equation section in Table 6.22. This shows that the p-value (0.000) was less than the critical value of 0.05. Therefore, it was concluded that the constant was not zero and the predicted odds of mobile money adoption for South Africa in Model 1 Block 0 were 0.790. The Score test displayed under the Variables not in the Equation section in Table 6.22 reveals that the p-value of the use of social media variable (0.000) was statistically significant at 5%, and the addition thereof to the null model would therefore improve the predictive strength of the model. The overall statistics p-value of 0.000 was significant at the 5% level.

Model 1 Block 1 displays the results of the binary logistic regression model following the addition of the use of social media to the intercept-only model (see Table 6.23 below).

Table 6.23: South Africa Model 1 Block 1

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	37.478	1	.000
	Block	37.478	1	.000
	Model	37.478	1	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	705.952[a]	.118	.154

a. Estimation terminated at iteration number 8 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	.000	0	.

Classification Table[a]

Observed			Predicted: Mobile money adoption: Non-adoption of Mobile Money technology	Predicted: Mobile money adoption: Mobile Money Adoption	Predicted: Percentage Correct
Step 1	Mobile money adoption	Non-adoption of Mobile Money technology	4870	0	100.0
		Mobile Money Adoption	71	0	.0
	Overall Percentage				98.6

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Use of social media	1.314	.300	14.195	1	.000	3.721
	Constant	-.309	.168	8.414	1	.000	.734

a. Variable(s) entered on step 1: Use of social media.

Source: Author's compilation

The Omnibus tests of model coefficients give the result of the likelihood ratio test, indicating whether the addition of the use of social media to the null model contributes significantly to the model fit. The Omnibus tests of model coefficients in Table 6.23 above gave a Chi-Square of 37.478 on 1 df; the p-value of the block is 0.000, which is less than the 0.05 significance level. This means that Model 1 Block 1 model was a significant improvement on Model 1 Block 0: the use of social media positively and significantly influenced mobile money adoption in South Africa. The block and step p-values were equal to the model value since all variables (constant and independent) were entered at the same time.

The model summary in Table 6.23 shows that the addition of the use of social media variable to the null model reduced the -2 Log likelihood statistic to 705.952 from 743.430 (705.952 + 37.478 from the Omnibus tests of model coefficients) in the null model. Thus, a reduction of the -2 Log likelihood statistic in Model 1 Block 1 implies an improvement in the model fit following the addition of the independent variable. The Nagelkerke R^2 in Model 1 Block 1 shows that the use of social media accounted for 15.4% of the variance in mobile money technology adoption decisions in South Africa. This value is low, implying a poor fit of the model as 84.6% of the variance in the mobile money technology adoption decision was accounted for by other variables which were not included in the Block 1 model. However, the Nagelkerke R^2 cannot be compared to the coefficient of determination use in multiple regression analysis when accounting for the variance in the dependent variable. At a 95% confidence level, the Hosmer and Lemeshow test (see Table 6.23) showed no statistical significance as a result of the inclusion of only use social media in Model 1 Block 1, necessitating further blocks of the binary logistic regression estimation.

The false positive and false negative error rates in classification displayed in Table 6.23 indicate that the decision rule was correct in not predicting a false positive outcome. On the other hand, the decision rule predicted the non-adoption of mobile money technology 4941 times. This prediction was wrong 71 times, giving a false negative rate of 1.44% (71/4941); the overall model's correct classification was 98.6%.

In the Variables in the Equation section of the table, the B-values were the log-odds for the binary logistic regression equation for predicting mobile money adoption in South Africa, after the addition of the use of social media to the intercept-only model. In terms of the Wald test, the coefficient of the use of social media variable was statistically significant at the 95% confidence level, meaning that the use of social media was a significant predictor of mobile money technology adoption decision. It was concluded that the use of social media variable had a positive (B = 1.314) and statistically significant effect (p-value = 0.000) on mobile money adoption in South

Africa. Hence, for every one-unit increase in the use of social media, a 3.721 increase in the log-odds of mobile money adoption was expected. The fitted Model 1 Block 1 equation for South Africa is shown below:

$$\text{Mobile money adoption} = -0.309 + 1.314 \times \text{Use of social media} \qquad (13)$$

6.3.2.2 Model 2

The second model comprises the use of social media and mobile money adoption × use of social media (the interaction term). The interaction term captured how the overall mobile money adoption would be increased by the simultaneous adoption of mobile money technology and use of social media. As in Model 1, Model 2 is presented in dual form - that is Block 0 and Block 1. The null model, Model 2 Block 0 is shown in Table 6.24 below.

Table 6.24: South Africa Model 2 Block 0

Classification Table[a,b]

Observed			Predicted: Mobile money adoption: Non-adoption of Mobile Money technology	Predicted: Mobile money adoption: Mobile Money Adoption	Predicted: Percentage Correct
Step 0	Mobile money adoption	Non-adoption of Mobile Money technology	4870	0	100.0
		Mobile Money Adoption	71	0	.0
	Overall Percentage				98.6

a. Constant is included in the model. b. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-.236	.183	11.391	1	.000	.790

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	Use of social media	35.895	1	.000
		Mobile money adoption × Use of social media	945.348	1	.000
	Overall Statistics		957.621	2	.000

Source: Author's compilation

Table 6.24 above reveals that, given the base rates of the two decision options (71/4941 = 1.44% chose to adopt mobile money and 98.6% did not), and with no other information, the best strategy was to predict for every case that an individual would choose to adopt mobile money. Using this strategy, the model would be correct 98.6% of the time. Thus, the overall percentage of cases that were correctly predicted by the null was 98.6%, and it could be concluded that the model was valid, a good fit for the data and replicable.

In the Variables in the Equation section, the Wald Chi-square tests show that the null hypothesis was to be rejected as the p-value (0.00) was less than the critical value of 0.05. Therefore, it was concluded that the constant was not zero and that the predicted odds of mobile money adoption for South Africa in Model 2 Block 0 were 0.790. The Score test under the Variables not in the Equation section in Table 6.24 shows that the use of social media and the interaction term (Mobile money adoption × Use of social media) were both statistically significant at a 95% confidence level, with a p-value of 0.000. The overall statistics' p-value of 0.000 reveals the result of including the two variables to the null model; based on this statistic, it was concluded that they significantly determined mobile money adoption at the 5% level. Therefore, the addition of the use of social media and the interaction term (mobile money adoption × use of social media) resulted in an improvement in the predictive strength of the model.

Table 6.25 below captures the outcome of the binary logistic regression model in Model 2 Block 1 after the addition the use of social media and the interaction term (mobile money adoption × use of social media) to the null model.

Table 6.25: South Africa Model 2 Block 1

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	168.065	2	.000
	Block	168.065	2	.000
	Model	168.065	2	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	575.366[a]	.658	.777

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	.000	1	.792

Classification Table[a]

Observed			Predicted: Mobile money adoption: Non-adoption of Mobile Money technology	Predicted: Mobile money adoption: Mobile Money Adoption	Predicted: Percentage Correct
Step 1	Mobile money adoption	Non-adoption of Mobile Money technology	4870	0	100.0
		Mobile Money Adoption	57	14	19.7
	Overall Percentage				98.8

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Use of social media	1.142	.283	31.026	1	.003	3.133
	Mobile money adoption × Use of social media	1.606	.342	39.192	1	.000	4.983
	Constant	-.372	.168	8.614	1	.000	.689

a. Variable(s) entered on step 1: Use of social media, Mobile money adoption × Use of social media

Source: Author’s compilation

The Omnibus tests of model coefficients (see Table 6.25 above) reflects a Chi-Square of 168.065 on df 2, and a p-value of the block (mobile money adoption × use of social media; use of social media) of 0.000, which is therefore statistically significant at the 95% confidence level. Thus, Model 2 Block 1 was a significant improvement on Model 2 Block 0 as the addition of the use of social media and the interaction term significantly and positively influenced mobile money technology adoption in South Africa. The block and step p-values were equal to the model's value since all variables (interaction term, use of social media and the constant) were entered at the same time.

The model summary in Model 2 Block 1 shows that the addition of the interaction term to the null model led to a decrease in the -2 Log likelihood statistic from 743.431 in Block 0 (575.366 + 168.065 from the Chi-square in the Omnibus tests of model coefficients) to 575.366. A reduction in the -2 Log likelihood statistic therefore indicated an improvement in the model fit. The Nagelkerke R^2 value indicated a good fit of the model as the use of social media and the interaction term (mobile money adoption × use of social media) explained 77.7% of the total amount of variance in the mobile money technology adoption decision in South Africa. Therefore, 22.3% of the total variance in mobile money adoption was accounted for by other variables which were excluded from Model 2 Block 1.

At a 95% confidence level, the Hosmer-Lemeshow test was not statistically significant (p-value = 0.792), however. Hence, in keeping with Hosmer and Lemeshow (2000), this indicates that the binary logistic regression was an adequate fit to the data since it had a p-value that was greater than the 0.05 significance level. The classification of the false positive and false negative error rates displayed in Table 6.25 above indicate that the decision rule predicted a decision of mobile money technology adoption 14 times; there was thus no false positive. The decision rule predicted the non-adoption of mobile money (false negative) 4927 times, and that prediction was wrong 57 times for a false negative of 1.16% (57/4927). The overall model correct classification was 98.6%.

As far as the Wald test from the Variables in the Equation section is concerned, the coefficients of mobile money adoption × use of social media (interaction term) and use of social media variables were statistically significant at the 95% confidence level. Using the Wald test statistic, it was concluded that both the interaction term (B = 1.606 and p-value of 0.00) and social media (B = 1.142 and p-value of 0.003) had a positive and statistically significant effect on the mobile money adoption decision in South Africa. Thus, for every one-unit increase in the interaction term, a 4.983 increase in the log-odds of overall mobile adoption was expected, holding the use of social media constant. Also, for every one-unit increase in the use of social media, a 3.133 increase in the log-odds of mobile money adoption was expected, holding the interaction term constant. The fitted Model 2 Block 1 equation for South Africa is shown below:

$$\text{Mobile money adoption} = -0.372 + 1.142 \times \text{Use of social media} + 1.606 \times \text{Mobile money adoption} \times \text{Use of social media} \tag{14}$$

6.3.2.3 Model 3

The third model is the full model that comprises the use of social media, the interaction term and five control variables parsimoniously determined from the principal components analysis procedure (age, gender, marital status, employment status and personal monthly income). Similar to the other models, Model 3 consists of two parts - Block 0 and Block 1. Model 3 Block 0, the null model is shown below in Table 6.26 and explained thereafter.

Table 6.26: South Africa Model 3 Block 0

Classification Table [a,b]

Observed			Predicted: Mobile money adoption: Non-adoption of Mobile Money technology	Predicted: Mobile money adoption: Mobile Money Adoption	Predicted: Percentage Correct
Step 0	Mobile money adoption	Non-adoption of Mobile Money technology	4870	0	100.0
		Mobile Money Adoption	71	0	.0
	Overall Percentage				98.6

a. Constant is included in the model.

b. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-.236	.183	11.391	1	.000	.790

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	Use of social media	235.895	1	.000
		Mobile money adoption × Use of social media	455.348	1	.000
		Age	61.858	1	.001
		Marital status	201.004	1	.010
		Employment status	57.508	1	.006
		Personal monthly income	19.256	1	.000
		Gender	6.171	1	.013
Overall Statistics			1502.716	7	.000

Source: Author’s compilation

The classification table in Table 6.26 above displays how the null model predicted mobile money adoption in South Africa. Given the base rates of the two decision options (71/4941 = 1.44% chose to adopt mobile money and 98.6% did not), and with no other information, the best strategy was to predict for every case that an individual would choose to adopt mobile money. Using this strategy, the model would be correct 98.6% of the time. Thus, the overall percentage of cases that were correctly predicted by the null was 98.6%, and it could be concluded that the model was valid, a good fit for the data and was replicable. The Wald test results in the

Variables in the Equation section in Table 6.26 show that the p-value (0.000) was less than the critical value of 0.05. Therefore, it was concluded that the constant was not zero and the predicted odds of mobile money adoption for South Africa in Model 1 Block 0 were 0.790. The Score test results displayed under the Variables not in the Equation section in Table 6.26 predicted the significance of adding all the explanatory variables to the null model. Looking at the p-values, in addition to the use of social media and the interaction term, all five of the selected control variables were all statistically significant at 5%. The overall statistics' p-value of 0.000 indicates that a full model led to a better fit as the statistic was less than the 0.05 significance level.

Table 6.27 below presents Model 3 Block 1, the outcome of the full binary logistic regression model. These results are discussed below.

Table 6.27: South Africa Model 3 Block 1

Omnibus Tests of Model Coefficients

		Chi-square	Df	Sig.
Step 1	Step	339.349	7	.000
	Block	339.349	7	.000
	Model	339.349	7	.000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	404.081[a]	.510	.783

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	Df	Sig.
1	2.459	8	.977

Classification Table[a]

Observed			Predicted: Mobile money adoption: Non-adoption of Mobile Money technology	Predicted: Mobile money adoption: Mobile Money Adoption	Predicted: Percentage Correct
Step 1	Mobile money adoption	Non-adoption of Mobile Money technology	4870	0	100.0
		Mobile Money Adoption	14	57	80.3
	Overall Percentage				99.7

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Use of social media	1.067	.219	18.096	1	.000	2.907
	Mobile money adoption × Use of social media	1.481	.265	24.717	1	.000	4.397
	Age	-.261	.493	6.258	1	.927	.770
	Marital status	.104	.281	10.429	1	.143	1.109
	Employment status	.649	.184	13.145	1	.000	1.913
	Personal monthly income	.531	.152	11.890	1	.003	1.700
	Gender	.486	.566	7.738	1	.001	1.626
	Constant	-.406	.192	8.404	1	.000	.666

a. Variable(s) entered on step 1: Use of social media, Mobile money adoption × Use of social media, Age, Marital status, Employment status, Personal monthly income, Gender.

Source: Author's compilation

The Omnibus tests of model coefficients (see Table 6.27 above) provided a Chi-square of 339.349 on 7 df, and the p-value of the block (full model after the addition of control variables) was 0.000, and thus statistically significant at the 95% confidence level. This meant that Model 3 Block 1 was a significant improvement on Model 3 Block 0 and the addition of control variables positively and significantly influenced mobile money adoption in South Africa. The block and step p-values are equal to the model value since all variables were entered at the same time.

The “Model Summary” section in Table 6.27 shows that the inclusion of the control variables to the null model led to a decrease of the -2 Log likelihood statistic from 743.43 in the null model (that is 404.082 + 339.349 from the Chi-square in the Omnibus tests of model coefficients) to 404.081. Therefore, a reduction in the -2 Log likelihood statistic implied an improvement in the predictive strength of the full model.

Although it cannot be compared to the coefficient of determination in multiple regression, the Nagelkerke R^2 statistic for the full binary logistic regression accounts for 78.3% of the total amount of variance in the mobile money technology adoption decision. The Nagelkerke R^2 value indicates a good fit of the model because only 21.7% of the variance in mobile money adoption was accounted for by other variables that were excluded from Model 3 Block 1. At a 95% confidence level, the Hosmer-Lemeshow test was, however, not statistically significant (p-value = 0.997), and in keeping with Hosmer and Lemeshow (2000), this result implied that the binary logistic regression was an adequate fits to the data because it had a p-value that was greater than the 0.05 significance level.

The classification of the false positive and false negative error rates displayed in Table 6.21 above shows that the decision rule correctly predicted a decision to adopt mobile money technology 57 times, thus giving no false positive. The decision rule predicted the non-adoption of mobile money 4884 times, and that prediction was wrong 14 times, for a false negative of 0.29% (14/4884). The overall model’s correct classification in Model 3 Block 0 was 99.7%. In Table 6.27, the Wald test in the Variables in the Equation section indicates that age and marital status were not significantly different from 0 since their p-values were greater than the 5% and 10%

significance levels (0.927 and 0.755 respectively). The dominant variables were the interaction term (mobile money adoption × use of social media), use of social media, employment status, personal monthly income and gender. The coefficients of these variables were all statistically significant at the 95% confidence level, and were therefore significant predictors of mobile money technology adoption in South Africa.

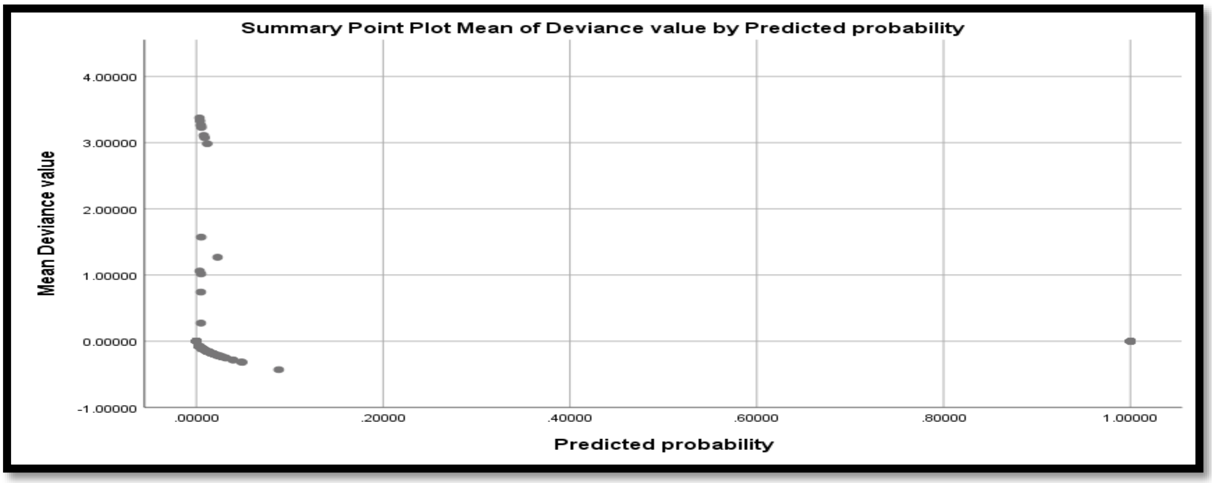
Thus, in South Africa, for every unit increase in the interaction term (B = 1.481), a 4.397 increase in the log-odds of mobile money adoption was expected, holding all other explanatory variables constant. Also, for every unit increase in the use of social media (B = 1.067), a 2.907 increase in the log-odds of mobile money adoption was expected, holding all other explanatory variables constant. The significant control variables showed that according to employment status, (B = 0.649) employed adults had a greater likelihood of mobile money adoption as a one-unit increase in employment increased the log-odds of mobile money technology adoption by 1.913, holding all other explanatory variables constant. All other explanatory variables held constant; a unit increase in personal monthly income (B = 0.531) led to an increase in the log-odds of mobile money adoption of 1.700. In terms of gender, (B = 0.486) a unit increase in males resulted in an increase in the log-odds of mobile money technology adoption by 1.626. Thus, the fitted Model 3 Block 1 equation for South Africa is as follows:

Mobile money adoption = -0.406 + 1.067 × Use of social media + 1.481 Mobile money adoption × Use of social media - 0.261 × Age + 0.104 × Marital status + 0.649 × Employment status + 0.531 × Personal monthly income + 0.486 Gender
(15)

6.3.2.4 South Africa full model diagnosis - deviance

A plot of the mean deviance residuals against the probability, showing how the full model (Model 3 Block 1) fitted the data is provided in Figure 6.6 below. The model is good if and only if the plotted values are between -3 and 3 (Mekonnen, 2011).

Figure 6.6: South Africa model fit by deviance



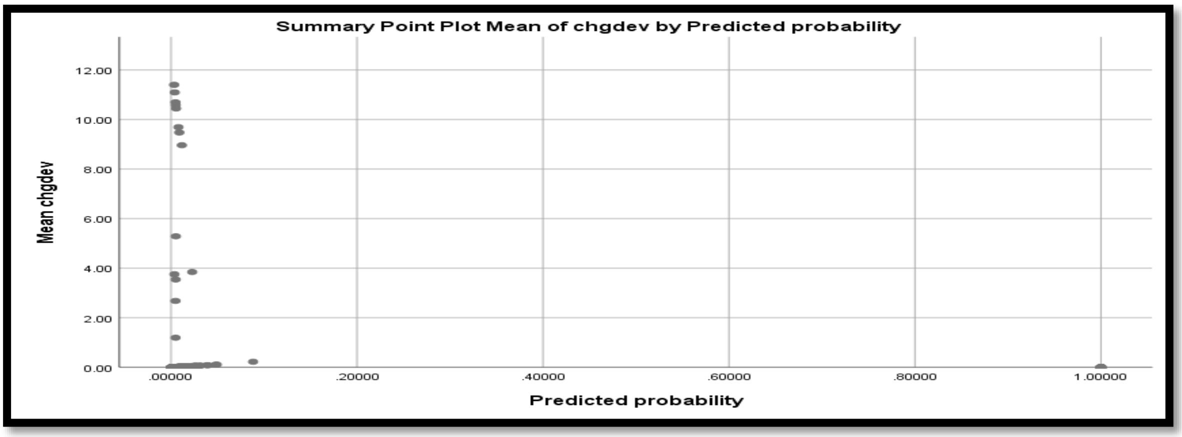
Source: Author's compilation

In Figure 6.6, the summary of the deviance shows that the data were almost crowded around zero, with some between 0 and 2, and only a few points at or above 3. Therefore, using the plot of mean deviance against predicted probability, it was concluded that the model was a moderate fit for the data.

6.3.2.5 South Africa full model diagnosis - model predicted probabilities

Additional analysis of the model fit to the data was undertaken by plotting the mean deviance against the predicted probability of mobile money adoption or otherwise. The resultant model fit for South Africa is displayed in Figure 6.7 and explained below.

Figure 6.7: South Africa model fit predicted probabilities



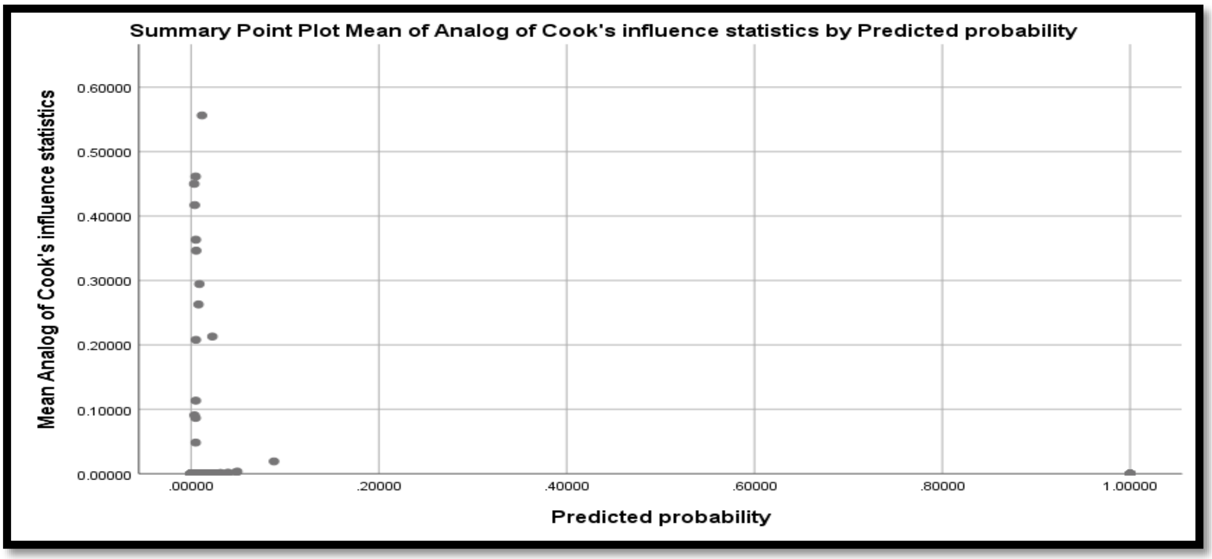
Source: Author's compilation

Figure 6.7 shows that the model is not good as not all plotted values lie between -3 and 3. This result therefore implied that that there are some other variables from literature which could have been included in the model to account for the adoption of mobile money adoption in South Africa.

6.3.2.6 South Africa full model diagnosis - Cook’s distance

A summary point plot showing the fit of the model by a measure of the Cook’s influence statistics against the predicted probability for South Africa is provided in Figure 6.8 below.

Figure 6.8: South Africa full model fit - Cooks distance



Source: Author’s compilation

The Cook’s distance is useful for spotting cases that unduly influence the binary logistic model, and observations of Cook's distance greater than 1 are considered to be influential outliers (Mekonnen, 2011). In Figure 6.6, the Cooks distance plotted against the predicted probability shows that the model fits the data because the mean analog of the Cook’s influence are less than 1, and lie between 0 and 0.6 Therefore according to the statistic, the full model (Model 3 Block 1) was a good fit for the data.

6.4 ROBUSTNESS CHECKS

After allowing the data to be subjected to a binary logistic regression model, the results were compared with those from the binary probit regression estimation technique, following the lead of Murendo et al. (2015a) and Kikulwe et al. (2014) who conducted closely related studies in East Africa.

6.4.1 Binary probit regression Zimbabwe

The results from the binary probit regression estimation for Zimbabwe are provided in Table 6.28 and discussed below.

Table 6.28: Binary Probit Model Zimbabwe

Model Information			
Dependent Variable	Mobile money adoption[a]		
Probability Distribution	Binomial		
Link Function	Probit		
a. The procedure models Non-adoption of Mobile Money technology as the response, treating Mobile Money Adoption as the reference category.			
Goodness of Fit[a]			
	Value	Df	Value/df
Model Deviance	374.083	8	.000
Residual Deviance	13.119	8	0.119
Total deviance (corr)	387.202		
Percentage of deviance explained by the model = 87.439% Adjusted percentage = 86.031%			
Dependent Variable: Mobile money adoption Model: (Intercept), Household location, Age, Gender, Marital status, Bank account ownership, Use of social media, Mobile money adoption × Use of social media (Interaction term)[a]			
a. Information criteria are in smaller-is-better form.			
Omnibus Test[a]			
Likelihood Ratio Chi-Square	Df	Sig.	
1640.710	7	.000	
Dependent Variable: Mobile money adoption Model: (Intercept), Household location, Age, Gender, Marital status, Bank account ownership, Use of social media, Mobile money adoption × Use of social media (Interaction term)[a]			
a. Compares the fitted model against the intercept-only model.			
Tests of Model Effects			
Source	Type III		

	Wald Chi-Square	Df	Sig.
(Intercept)	13.976	1	.000
Household location	77.721	1	.000
Age	9.296	1	.443
Gender	4.961	1	.026
Marital status	10.629	1	.107
Bank account ownership	69.747	1	.000
Use of social media	175.528	1	.000
Mobile money adoption × Use of social media (Interaction term)	193.849	1	.000
Model: (Intercept), Household location, Age, Gender, Marital status, Bank account ownership, Use of social media, Mobile money adoption × Use of social media (Interaction term)			

Parameter Estimates

Parameter	B	Std. Error	Hypothesis Test			Exp(B)
			Wald Chi-Square	df	Sig.	
(Intercept)	-.315	.147	13.976	1	.000	.730
Household location	-.325	.161	77.721	1	.000	.723
Age	-.213	.083	9.296	1	.443	.808
Gender	-.290	.174	4.961	1	.026	.748
Marital status	-.063	.042	10.629	1	.107	.939
Bank account ownership	-.180	.073	69.747	1	.000	0.835
Use of social media	0.624	.461	175.528	1	.000	1.866
Mobile money adoption × Use of social media (Interaction term)	1.003	.076	193.849	1	.000	2.726

Source: Author's Compilation

Table 6.28 shows that the goodness of fit of the binary probit model to the Zimbabwean data. The deviance is decomposed into an explained (model) and an unexplained (residual) component. The deviance compares the likelihood function for the model to the largest value that the likelihood could achieve, in such a manner that a perfect model would have a deviance equal to 0.

There are three figures displayed for the deviance in Table 6.28: the model, residual and total. Firstly, the model deviance is the reduction in the deviance owing to the predictor variables identified for the study (household location, age, gender, marital status, bank account ownership, use of social media, mobile money adoption × use of social media). Secondly, the residual deviance refers to the deviance remaining after the model has been fit. Thirdly, the total (corr.) is the deviance of a model containing only an intercept (constant) term. The p-value for the model deviance tests whether the addition of the seven predictor variables identified above significantly reduced the deviance, when compared to a model containing only an intercept term. The binary probit regression results for Zimbabwe show a small p-value (0.000) operating at the 5% significance level. This result therefore indicates that the addition of the seven identified predictor variables to the intercept-only model significantly reduced the deviance. Hence, the model with the added predictor variables was a good fit for the data, and was useful for predicting the probability of mobile money technology adoption in Zimbabwe.

The p-value for the residual term tests whether there is significant lack-of-fit, that is whether a better model may still be possible following the addition of the identified seven predictor variables to the intercept-only model. A p-value of less than 0.05 (at the 95% confidence level) would indicate that a significant amount of deviance remains in the residual, so that a better model might be possible. Table 6.28 shows a p-value for the residual of 0.119, which is greater than 0.05 significance level, thus according to the statistic, a better model fit beyond the addition of the study's identified predictor variables was impossible. Hence, it was concluded that the estimated binary probit model was a good fit for the data.

The percentage of deviance (87.44%) and adjusted percentage of deviance (86.03%) shown in Table 6.28 above are the pseudo R^2 that are similar to the R^2 in multiple regression. The high value of the adjusted percentage of deviance statistic thus implies a good fit of the model to the data as the binary probit model employed for the study accounted for 86.03% of the total variance in mobile money adoption in Zimbabwe. Only 13.97% of the total variance was explained by other variables that were excluded from the study. The Omnibus test of model coefficients gives the result of the likelihood ratio test of significance, indicating whether the addition of the seven explanatory variables to the intercept (constant) only model contributed significantly to the model fit. Table 6.28 above indicates that the full binary probit model output for Zimbabwe gave a Chi-Square of 1640.710 on 1 df, and a p-value of 0.000 which was less than the 0.05 significance level. This meant that the binary probit model consisting of all the explanatory variables employed in the present study was a good fit to the data and a significant improvement on the intercept-only model. This result was similar to that obtained from the full binary logistic regression model estimation (see Model 3 Block 1 in Table 6. 21).

The Tests of Model Effects section in Table 6.28 above indicates that age and marital status were the only variables not statistically different from zero as their p-values were insignificant at both the 95% and 90% confidence levels. Similar to the binary logistic regression model output under Model 3 Block 1 in Table 6.21, the Parameter Estimates section in Table 6.28 shows that the statistically significant determinants of mobile money technology adoption in Zimbabwe were the use of social media, interaction term, gender, bank account ownership and household location. The coefficients of these variables were all statistically significant at the 95% confidence level under the binary probit regression analysis. Thus, holding all other explanatory variables constant, for every unit increase in the use of social media (B = 0.624), a 1.866 increase in mobile money technology adoption was predicted. Holding all other explanatory variables constant, a unit increase in Mobile money adoption × Use of social media (B = 1.003) led to a 2.726 increase in adoption of mobile money technology.

When considering gender, (B = -0.290), it was envisaged that holding other explanatory variables constant, a unit increase in males would lead to reduced adoption of mobile money services by 0.748. It was thus concluded that in Zimbabwe, males had a lower likelihood of adopting the financial innovation than females. Similarly, holding all other explanatory variables constant, a unit increase in bank account ownership (B = -0.180) resulted in a decline in mobile money technology adoption by 0.835. In addition, keeping all other explanatory variables constant, it was expected that for every unit increase in urbanites (B = -0.325), there would be a reduction in mobile money adoption by 0.723. Therefore, the rural population was more likely to take up mobile money services in Zimbabwe. The fitted binary probit model for mobile money adoption by an individual in Zimbabwe is shown below:

Mobile Money Adoption = -0.395 + 0.624 × Use of social media + 1.003 × Mobile money adoption × Use of social media – 0.290 × Gender – 0.213 × Age - 0.063 ×

Marital status – 0.180 × Bank account ownership – 0.325 × Household location (16)

6.4.2 Binary probit regression South Africa

Table 6.29 displays the output from the binary probit regression estimation for South Africa, with a discussion of the results below.

Table 6.29: Binary Probit Model South Africa

Model Information	
Dependent Variable	Mobile money adoption
Probability Distribution	Binomial
Link Function	Probit

a. The procedure models Non-adoption of Mobile Money technology as the response, treating Mobile Money Adoption as the reference category.

Goodness of Fit[a]

	Value	Df	Sig.
Model Deviance	294.204	8	.044
Residual Deviance	10.918	8	.153
Total Deviance (corr)	305.122		

Percentage of deviance explained by the model = 74.694%

Adjusted percentage = 72.853%

Dependent Variable: Mobile money adoption

Model: (Intercept), Age, Gender, Marital status, Personal monthly income, Employment status, Use of social media, Mobile money adoption × Use of social media (Interaction term)

a. Information criteria are in smaller-is-better form.

Omnibus Test[a]

Likelihood Ratio Chi-Square	Df	Sig.
404.007	7	.000

Dependent Variable: Mobile money adoption

Model: (Intercept), Age, Gender, Marital status, Personal monthly income, Employment status, Use of social media, Mobile money adoption × Use of social media (Interaction term)

a. Compares the fitted model against the intercept-only model.

Tests of Model Effects

Source	Type III		
	Wald Chi-Square	Df	Sig.
(Intercept)	11.750	1	.000
Age	10.247	1	.114
Gender	6.841	1	.002
Marital status	9.296	1	.488
Personal monthly income	11.913	1	.001

Employment status	15.140	1	.008
Use of social media	20.854	1	.000
Mobile money adoption × Use of social media (Interaction term)	23.528	1	.000

Parameter Estimates

Parameter	B	Std. Error	Hypothesis Test			Exp(B)
			Wald Chi-Square	df	Sig.	
(Intercept)	-.250	.092	11.750	1	.000	.779
Age	-.158	.083	10.247	1	.114	.854
Gender	.295	.098	6.841	1	.002	1.343
Marital status	.125	.074	9.296	1	.488	1.133
Personal monthly income	.322	.238	11.913	1	.001	1.343
Employment status	.393	.275	15.140	1	.008	1.481
Use of social media	.650	.342	20.854	1	.000	1.916
Mobile money adoption × Use of social media (Interaction term)	.900	.578	23.528		.000	2.460

Source: Author's compilation

The goodness of fit for South Africa using the binary probit model (Table 6.29 above) was decomposed into an explained (model) and an unexplained (residual) component. As was the case for Zimbabwe, there are three figures displayed for the deviance: (1) the model deviance, which is the reduction in the deviance owing to the predictor variables identified for the study (age, gender, marital status, personal monthly income, employment status, use of social media and mobile money adoption × use of social media), (2) the residual deviance, and (3) the total deviance of a model containing only an intercept (constant) term.

As reflected in Table 6.29, the binary probit regression model for South Africa had a small p-value (0.000) at the 95% confidence level. This outcome indicates that the addition of the seven identified predictor variables to the intercept-only model significantly reduced the deviance. Therefore, it was concluded that the model with the identified predictor variables was a good fit for the data, and was therefore useful in predicting the probability of the adoption of mobile money technology in South Africa.

The p-value for the residual term sought to test whether there was significant lack-of-fit, that is whether a better model might still have possible following addition of the seven predictor variables to the intercept-only model. A p-value less than 0.05 (operating at the 5% significance level) therefore means that a significant amount of deviance remained in the residual, and so, a better model fit might have been possible. Table 6.29 above shows a p-value for the residual deviance of 0.103, a result greater than the 0.05 significance level. Thus, according to the statistics it would not have been possible for the study to obtain a meaningfully improved model fit beyond the addition of the identified study predictor variables. Accordingly, it was concluded that the binary probit model estimation used in the current study was a good fit for the data.

The percentage of deviance (74.69%) and adjusted percentage of deviance (72.85%) displayed in Table 6.29 above are the pseudo R^2 that are similar to the R^2 in multiple regression. The high value of the adjusted percentage of deviance statistic thus implied a good fit of the model to the data as the binary probit model employed for the study accounted for 72.85% of the total variance in mobile money adoption in South Africa. Only 27.15% of the total variance in mobile money adoption was explained by other variables that were not included in the present study. The Omnibus test of model coefficients provides the result of the likelihood ratio test of significance, indicating whether the addition of the seven explanatory variables to the intercept (constant) only model contributed significantly to the model fit. Looking at Table 6.29 above, the binary probit model output for South Africa gave a Chi-Square of 404.007 on 7 df, and a p-value of 0.000, which was less than the 0.05 significance level. This means that the binary probit model consisting of all the explanatory variables employed in the study was a good fit to the data, and a significant improvement on the intercept-only model, a similar results to that obtained from the binary logistic regression model estimation shown in Model 3 Block 1 (see Table 6.27).

The Tests of Model Effects section in Table 6.29 shows that age and marital status were not statistically different from zero because their p-values are insignificant at both the 5% and 10% significance levels. Similar to the binary logistic regression model output under Model 3 Block 1 in Table 6.27, the Parameter Estimates section in Table 6.29 shows that the statistically significant determinants of mobile money technology adoption in South Africa were the use of social media, mobile money adoption × use of social media (interaction term), gender, personal monthly income and employment status. The coefficients of these variables were all statistically significant at the 5% level, using the binary probit model estimation technique. Therefore, keeping all other explanatory variables constant, for every unit increase in the use of social media (B = 0.650), a 1.916 times increase in mobile money technology adoption was anticipated. Also holding all other explanatory variables constant, a unit increase in the interaction term (Mobile money adoption × Use of social media) (B = 0.9000) would result in a 2.460 increase in mobile money adoption.

With respect to gender (B = 0.295), it was anticipated that holding other explanatory variables constant, a unit increase in males would result in a 1.343 increase in the likelihood of mobile money services' adoption. Therefore, it was determined that in South Africa, men were more likely to take up the financial innovation than women. Similarly, holding all other explanatory variables constant, a unit increase in bank account ownership (B = -0.180) resulted in a decline in mobile money technology adoption of 0.835. In addition, keeping all other explanatory variables constant, it was expected that every a unit increase in the number of South African adults that had a personal monthly income (B = 0.322) would lead to a 1.380 increase in adoption of the financial innovation. Also, a unit increase in the number of employed adults (B = 0.393) was expected to increase the likelihood of mobile money services adoption in South Africa 1.481 times. The fitted binary probit model for mobile money adoption by an individual in South Africa is shown below:

$$\text{Mobile Money Adoption} = -0.250 + 0.650 \times \text{Use of social media} + 0.900 \times \text{Mobile money adoption} \times \text{Use of social media} + 0.295 \times \text{Gender} - 0.158 \times \text{Age} + 0.125 \times \text{Marital status} + 0.322 \times \text{Personal monthly income} + 0.393 \times \text{Employment status} \quad (17)$$

A comparison of the results from the binary probit and the binary logistic models corroborated findings in literature (Fenella, 2016; Lewbel et al., 2012; Patnaik and

Sharma, 2013 Cakmakyapan and Goktas, 2013; Greene, 2012). Despite the variances in the scaling of parameters, the estimators in the binary logistic and probit models that were applied to predict mobile money technology adoption in Zimbabwe and South Africa nevertheless led to the same standardised impacts of the predictor variables (signs and statistical significance), and hence similar results were obtained. Therefore, the study concluded that the estimated binary logistic and binary probit models were an identical fit to the FinScope consumer survey South Africa 2015 and Zimbabwe 2014 data sets. The results obtained from the binary probit regression model estimations are thus robust for both countries.

6.5 SUMMARY OF EMPIRICAL FINDINGS

A summary of the empirical findings from the binary logistic regression for Zimbabwe and South Africa is provided in Table 6.30 below. It features Models 1, 2 and 3, their respective blocks, and the changes between the models. A discussion of the differences in the models within countries and between the two countries follows thereafter.

Table 6.30: Summary of changes in binary logistic models

Country	Model	Block 0	Block 1	Change
Zimbabwe	Model 1 (Use of social media): • Classification Table overall %. • -2 Log Likelihood. • Nagelkerke R^2.	 51% 5196.982 -	 65.3% 4754.847 16.8%	 14.3% 442.134 -
	Model 2 (Use of social media + Interaction term): • Classification Table overall %. • -2 Log Likelihood. • Nagelkerke R^2.	 51% 5196.982 -	 94.1% 3703.699 89.2%	 43.1% 1493.283 ** 72.4%
	Model 3 (Use of social media + Interaction term + Control variables): • Classification Table overall %. • -2 Log Likelihood. • Nagelkerke R^2	 51% 5196.982 -	 94.1% 3556.008 89.8%	 43.1% 1640.974 *** 0.6%

South Africa	Model 1 (Use of social media): • Classification Table overall %. • -2 Log Likelihood. • Nagelkerke R^2.	98.6% 743.43 -	98.6% 705.952 15.4%	0.0% 37.478 -
	Model 2 (Use of social media + Interaction term): • Classification Table overall • -2 Log Likelihood • Nagelkerke R^2	98.6% 743.43 -	98.8% 575.366 77.7%	0.2% 168.065 ** 62.3%
	Model 3 (Use of social media + Interaction term + Control variables): • Classification Table overall % • -2 Log Likelihood • Nagelkerke R^2	98.6% 743.43 -	99.7% 404.081 78.3%	1.1% 339.349 *** 0.6%
** Nagelkerke R^2 change = Model 2 Block 1 minus Model 1 Block 1 *** Nagelkerke R^2 change = Model 3 Block 1 minus Model 2 Block 1				

Source: Author's compilation

6.5.1 Summary of binary logistic regression Zimbabwe

A comparison across models for Zimbabwe (from Model 1 Block 0 to Model 3 Block 1) reported several changes. Firstly, the Classification Table's overall percentage rose from 51% in Model 1 Block 0 to 65.3% in Model 1 Block 1, but despite indicating a significant fit in the model, remained constant at 94.1% in Model 2 Block 1 and Model 3 Block 1. Secondly, from Model 1 Block 0 to Model 3 Block 1, the -2 Log Likelihood statistics showed subsequent decreases from 5196.982 (Model 1 Block 0) to 3555.008 (Model 3 Block 1). This decline of the -2 Log Likelihood statistic throughout the three models was therefore an indicator of a good fit of the binary logistic model to the data.

Thirdly, when considering the Nagelkerke R^2 statistic, an appraisal of Model 1 Block 1 and Model 2 Block 1 revealed that the addition of the interaction term to the model led to a surge in the Nagelkerke R^2 by 72.4% from 16.8% in the former, to 89.2% in the latter. An assessment of the same statistic between Model 3 Block 1 and Model 2 Block 1 however indicated a slight change (0.6%) from 89.2% to 89.8%. it was thus concluded that in terms of the Nagelkerke R^2, the interaction term accounted for the greatest proportion of variation in mobile money adoption in Zimbabwe when compared to the use of social media (16.8%) and the control variables (0.6%). Hence, the overall proportion of mobile money technology adoption was indeed amplified where an adopter individual used both social media and mobile money technology.

6.5.2 Summary of binary logistic regression South Africa

A number of changes from Model 1 Block 0 through to Model 3 Block 1 in South Africa are displayed in Table 6.30. Firstly, in Model 1 Block 0 the Classification Table's overall percentage is 98.6% and remains static in Model 1 Block 1 but rises to 98.8% and 99.7% in Model 2 Block 1 and Model 3 Block 1 respectively, thus suggesting improvements to the model fit with the addition of the interaction term and control variables. Likewise, an improvement in the predictive strength of the full model is indicated by a decline in the -2 Log likelihood statistic from 743.43 (Model 1 Block 0) to 705.952 (Model 1 Block 1); 575.366 (Model 2 Block 1) to 404.081 (Model 3 Block 1). Similarly, the Nagelkerke R^2 statistic revealed increases in the total variance of mobile money technology adoption being explained across the models, from 15.4% in Model 1 Block 1, increasing by 62.3% following the inclusion of the interaction term to 77.7% in Model 2 Block 1. The addition of the control variables led, however, to a 0.6% increase in the Nagelkerke R^2 from 77.7% in Model 2 Block 1 to 78.3% in Model 3 Block 1.

6.5.3 Comparisons of results of binary logistic regression Zimbabwe and South Africa

A comparison of the changes in the three models in South Africa and Zimbabwe was undertaken using the information displayed in Table 6.30 above. First, the Classification Table's overall percentage and the Nagelkerke R^2 statistic between the two countries revealed some interesting outcomes. In Model 1, overall percentage difference in the Classification Table between Block 0 and Block 1 for Zimbabwe was larger (14.3%) than that of South Africa (0.0%), signalling a greater improvement of the model fit to the data in the former. Also, the addition of the use of social media in Model 1 resulted in a marginally higher Nagelkerke R^2 statistic for Zimbabwe (16.8%) than for South Africa (15.4%). Therefore, despite there being a lower overall social media penetration rate in Zimbabwe (26.1%) than in South Africa (45.2%), the use of social media accounted for a higher proportion of the total variance in mobile money technology adoption in the former.

Secondly, Table 6.30 shows that under Model 2, the change in the Classification Table's overall percentage from Block 0 to Block 1 in Zimbabwe was still higher (43.1%) than in South Africa (0.2%). According to the -2 Log Likelihood statistics substantial improvements in the models' mobile money technology prediction strength were established for both countries (as indicated by declines in the statistic) with each subsequent addition of the independent variable and interaction term and control variables from Model 1 Block 1 to Model 2 Block 1. A comparison of the Nagelkerke R^2 statistics in the two countries from Model 1 Block 1 to Model 2 Block 1 revealed that the inclusion of the interaction term resulted in a greater change in the amount of variation in mobile money technology adoption in Zimbabwe (72.4%) than in South Africa (62.3%). Therefore, based on the Nagelkerke R^2 statistic, it was concluded that the interaction term (mobile money adoption × use of social media) did increase the overall extent of mobile money technology adoption in both countries.

Thirdly, in terms of Model 3, the overall percentage change in the Classification Table overall for Zimbabwe from Model 3 Block 0 and Model 3 Block 1 was 43.1%. There was no change in the statistic when comparing Model 2 Block 1 and Model 3 Block 1, however. On the other hand, Table 6.22 showed that South Africa recorded a slight change in the Classification Table's overall percentage difference between: (1) Model 3 Block 0 and Model 3 Block 1 (1.1%), and (2) Model 2 Block 1 and Model 3 Block 1 (0.9%). The addition of the control variables led to an increase in the Nagelkerke R^2 statistic by a margin of 0.6% in the Model 3 Block 1 for both countries. This suggested an almost negligible contribution by the control variables to the total variance in mobile money adoption.

6.6 CHAPTER SUMMARY

This chapter has discussed the findings of the effect of social media, the interaction term and control variables under the binary logistic and probit models. In keeping with the theoretical predictions, the conclusion of the study was that that the use of social media was an important predictor of mobile money adoption in South Africa and Zimbabwe. The use of social media generated social learning, social contagion effects, social capital as well as introduced and diffused knowledge across network members, ultimately led to the adoption of mobile money technology. Despite Zimbabwe having a lower rate of social media usage than South Africa, findings suggested that the use of social media led to a greater likelihood of mobile money adoption in the former than the latter. Furthermore, the study showed that the interaction term (mobile money adoption × use of social media) increased the adoption of technology. The simultaneous use of social media and mobile money services accelerated the spread of information by adopters to non-adopters through online social networks. In turn, the non-adopters would follow the adopters, and eventually adopt the financial innovation. Again, the study found that the interaction term enhanced mobile money technology adoption more in Zimbabwe than in South Africa. The impact of each control variable on mobile money adoption in Zimbabwe and South Africa was shown and compared to theoretical predictions. Despite variations in scaling, the study found that the results (direction, nature, significance) of the use of social media, interaction term and control variables using the binary logistic and binary probit models were similar. The following chapter discusses the contribution of the study to new knowledge and provides conclusions, recommendations and suggestions for future research premised on the findings discussed in this chapter.

CHAPTER 7

DISCUSSION OF FINDINGS, CONCLUSIONS AND RECOMMENDATIONS

7.1 INTRODUCTION

Numerous empirical studies have examined the determinants of mobile money adoption in developing countries (Donovan, 2012; Kirui et al., 2012; Kikulwe et al., 2014; Ammar and Ahmed, 2016). A review of theoretical and empirical studies has shown that various technology acceptance and social networking theories acknowledge the substantial role of social influence in mobile financial technology adoption (Ajzen and Fishbein, 1975; Davis, 1989; Ajzen, 1991; Taylor and Todd, 1995; Rogers, 1995; 2003; Bandura, 1986; Burt, 1987; Alomary and Woollard, 2015; Mugambe, 2017; Ahmed, 2017; Ammann and Schaub, 2016). However, the review of the same literature also showed that the impact of social influences, specifically social networks, on financial technology adoption is rarely investigated in isolation. Notwithstanding, sparse empirical evidence from East Africa indicated that traditional offline social networks had a significant positive influence on mobile financial technology adoption.

In addition, reviewed literature for the purpose of this study indicates that no particular attention has to date been given to the role that social media plays in influencing mobile financial technology adoption despite indicate evidence that social media positively impacts on purchasing, savings, investing and crowdfunding behaviour (Nyagucha, 2017; Kosavinta et al., 2017; Makina, 2017; Beier and Wagner, 2017; Jashari and Rrustemi, 2017; Barhemmati and Ahmad, 2015). Of particular interest to the present study was the adoption of mobile money technology. Theoretical and empirical literature reviewed indicated that the adoption of mobile money technology, especially in developing economies improves financial inclusion, which in turn delivers sustainable equitable economic growth, poverty reduction, deeper financial intermediation, entrepreneurial ventures and better risk management (Demirgüç-Kunt et al., 2018; International Monetary Fund, 2016; Donovan, 2012; Dupas and Robinson, 2013a; Blumenstock et al., 2014; Murendo et al., 2015a; 2015b).

The main intention of this study was to investigate the effect of social media on mobile money adoption in South Africa and Zimbabwe. Particular attention was also given to comparisons of the impact of social media on mobile money adoption in the two countries. Chapter 6 provided the detailed findings of all these analyses. The findings revealed that the use of social media had a significant positive impact on mobile money adoption. The remainder of this chapter is organised as follows: section 7.2 discusses the empirical results of the study. Section 7.3 explains the contribution of the study to the body of knowledge. Section 7.4 draws conclusions from the study. Section 7.5 outlines the limitations of the study; section 7.6 provides recommendations while section 7.7 suggests areas for further research in accordance with the current findings.

7.2 DISCUSSION OF EMPIRICAL FINDINGS

Chi-square tests were undertaken (see Chapter 5) in order to determine the probable link between mobile money adoption and the use of social media. The results indicated a significant positive relationship between the two main variables in South Africa and Zimbabwe. The principal factor analysis procedure (see Chapter 6) identified age, gender, marital status, household location and bank account ownership as the control variables pertinent to an analysis of FinScope consumer survey Zimbabwe 2014 data set. On the other hand, employment status, individual monthly income, marital status, age and gender were selected as the most useful control variables for the FinScope consumer survey South Africa 2015 data set. Afterwards, the two data sets were subjected to regression modelling using the binary logistic and binary probit estimation techniques. The results obtained from the analyses were found to be robust; despite the scaling differences in the two estimation methods, the similarity in results confirmed the findings in literature (Cakmakyapan and Goktas, 2013; Fernando, 2011; Patnaik and Sharma, 2013; Verbeek, 2004; Long, 1997; Greene, 2012; Wittink. 2011).

Table 7.1 below provides a summary of the results of the study compared to expectations derived from prior empirical literature in Chapter 4 (see Table 4.3). A discussion of these results follows.

Table 7.1: Summary of expected and actual variable signs

Variable	Expected Sign	Theory Intuition and Source	Actual sign Zimbabwe	Actual sign South Africa
Use of social media	+	Nyagucha (2017); Kosavinta et al. (2017); Kavitha and Bhuvaneswari (2017); Beier and Wagner (2015).	+	+
Interaction term (Use of social media × Mobile money adoption)	+	Interaction term positively amplifies overall mobile money adoption (Author).	+	+
Age	-	Gamble et al. (2015); Choi et al. (2014); Jain and Mandot (2012).	-	-
Gender	+	Van Hove and Dubus (2019); Demirgüç-Kunt et al. (2018); Biscaye et al. (2017); FinMark Trust, (2016).	-	+
Marital status	+/-	Chattopadhyay and Dasgupta, (2015); Arano, Parker and Terry (2010); Christiansen et al. (2015).	-	+
Employment status	+/-	Chattopadhyay and Dasgupta (2015); Jain and Mandot, (2012); FinMark Trust (2016).	**N/A	+
Personal monthly income	+	Van Hove and Dubus (2019); FinMark Trust (2016); Murendo et al. (2015); Lasserre (2015); Faff et al., (2008).	**N/A	+
Household location	+	GSMA (2014); Lwanga and Adong (2016); Intermedia (2013).	-	**N/A
Bank account ownership	-	FinMark Trust (2016).	-	**N/A
**N/A = Variable not applicable to that particular country.				

Source: Author's compilation

7.2.1 Social media

Premised on findings from the literature, the use of social media was expected to have a positive influence mobile money technology adoption. The study found that the use of social media had a positive and statistically significant effect on mobile money adoption in both countries. This result thus suggests that the use of social media is essential in enabling the dissemination of knowledge and subsequent adoption of mobile money technology in South Africa and Zimbabwe. Thus, it was concluded that the use of social media platforms such as Facebook, Twitter, Instagram and WhatsApp, among others facilitated the mobile money innovation adoption decision process stages of knowledge acquisition, persuasion and adoption or rejection. Furthermore, the use of social media allowed real-time open discussions and reviews of mobile money technology attributes such as the relative advantages, compatibility, complexity and observability, trialability. Thus, online interactions resulted in the would-be adopters being better informed about the financial innovation prior to making an adoption decision.

The results of the study also suggested that use of social media promoted social learning, either from one's own direct experience, or from observing and imitating the behaviour of early mobile money technology adopters in one's online social network. Through observational learning from online social reviews and comments by current mobile money users, the non-adopters would imitate a chosen model's behaviour mobile money technology adoption decision. Social learning facilitated through the use of social media platforms thus allowed non-adopter individuals to: (1) follow an adopter model's behaviour online, (2) acquire and retain information on mobile money technology, (3) refine their skills in readiness of mobile money technology adoption, and (4) ultimately imitate the model's behaviour by adopting mobile money technology themselves. Consequently, non-adopters would take a positive cue from adopters providing useful information through shares, likes and tweets of positive reviews on mobile money technology such as convenience, low transaction costs, ease of use and low perceived risks.

The findings on the effect of use of social media on mobile money adoption were consistent with Fafchamps et al. (2017) and Mobius and Rosenblat (2014) who established that when people discussed about new products with others among their social networks, information about the existence of the new product would through social learning. Consequently, a proportion of non-adopters who became informed of the financial innovation would adopt it, since adoption requires knowing about the service and such knowledge was disseminated through online social platforms. The study's findings also validate the social contagion theory (Burt, 1987), which assumes that individuals in similar positions within a social network will evaluate the merits and risks of adoption similarly. Furthermore, the outcome of the study supports one theoretical underpinning of social media - Goffman's (1959) presentation of self theory, a concept that explains how an individual can impress his or her views on a chosen subject matter on others. Therefore, through social media platforms, an adopter individual conveys an impression of on mobile money technology to others and thereafter, other people will form an opinion about that particular individual and will decide to follow suit.

Likewise, the outcome of the study mirrors findings from other empirical research (Schwartz and Halegoua, 2015; Papacharissi, 2010; Edwards, 2015; Livingstone, 2008; Obee, 2012; Boyd, 2006), which note that people use online social networks to spread awareness of their interests and to impress them on their social media network group members. The results of this study are also similar to those of Qi (2018) who found that online sites that enabled messages on a subject matter to be viewed publicly across a platform, and to spread through likes (Facebook for instance) and re-shares (for example Twitter's re-tweet) were ideal and effective communication conduits to. Therefore, the use of social media allows people to make connections with any person on the network regardless of whether the people involved were acquainted in any other way; ultimately they influence each other's mobile money adoption decision.

Findings on the effect of social media usage on mobile money adoption also validate Bourdieu's (1977; 1992) social capital theory which reasons that the humans are social beings, and that their conduct is influenced by such social origins. In keeping with this theory, this study established that use of social media mediates the accumulation and spread of knowledge on mobile money technology through online social capital. The continuous exchange of information among group members on social media platforms therefore increases an individual’s access to, accumulation of and diffusion of information on mobile money technology. Subsequently, use of social media accelerates adoption of mobile money technology as information reaches many in real-time across geographies. The positive influence of the use of social media on mobile money adoption also resonates with findings by Evans (2015), Ellison, Steinfield and Lampe (2007) and Carrigan (2016) who found that sharing of information through online social platforms was an ideal way of amassing social capital from other network members. Hence, social media help diffuse, in real time, information on the merits of mobile money technology and ultimately influences their adoption decisions.

Although the present study departs from general financial behaviour and focuses on the mobile money technology adoption, the results mirror other more recent empirical work that established that online social networking platforms were being used by investors to gather and share investment information because they provided timely, firm-specific industry updates that were essential in the investment decision process (Kavitha and Bhuvaneswari, 2017; Heimer, 2016; Ammann and Schaub, 2016; Mudholkar and Uttarwar, 2015). The results of the present study are similar to those of empirical studies that have found that online social networking interactions strongly and positively influenced crowdfunding campaign successes (Makina, 2017; Beier and Wagner, 2015; Schwienbacher and Larralde, 2012; Giudici et al., 2013; Kerkhof, 2016).

The findings of the current study show that the use of social media increases an individual’s access to, accumulation and diffusion of information on mobile money, and subsequently accelerates adoption as information reaches many in real-time across geographies. It is therefore inferred that when non-adopter individuals interact on online platforms (for example Facebook, WhatsApp, Twitter) and chat about mobile money technology with adopters, they become more knowledgeable and accordingly undertake informed adoption decisions. Hence, the use of various social media platforms is a strong driver of mobile money technology adoption.

7.2.2 Interaction term

The present study found that the interaction of the social media use and mobile money adoption had a significant positive influence on mobile money adoption in South Africa and Zimbabwe. This result thus supports the author's earlier supposition that the overall amount of mobile money adoption in a country would be increased if an individual simultaneously used mobile money technology and online social networking platforms. The use of social media would then allow the adopter individuals to share their own experiences and benefits derived from adoption of the financial innovation, and in turn, non-adopters would follow suit. The ripple effects of the interaction term alone would thus intensify mobile money technology adoption more than if a mobile money adopter individual did not use social media and only relayed information about the financial innovation through narrow-focused traditional offline social networks (physical interaction, phone calls, text messages) whose reach is limited to his or her close social ties. The use of both mobile money technology and social media would thus enable an adopter individual to quickly and widely spread awareness and the relative advantages of the innovation through visual and audio formats to a large audience, beyond his or her social clique, cost effectively, in real time, thereby increasing overall adoption rates.

7.2.3 Other determinants of mobile money adoption

The current study found that age had a negative but insignificant influence on mobile money technology adoption in South Africa and in Zimbabwe. In summary, young adults were more likely to adopt mobile money services than the older generations. These findings are generally similar to those of other researchers (Maheshwari and Mittal, 2017; Onsomu, 2015; Gamble et al., 2015; Lachs and Han, 2015; Korniotis and Kumar, 2011; Jain and Mandot, 2012) who established a deterioration in financial decision-making with advances in age. These findings also resonate with Samanez-Larkin et al. (2010) and Choi et al. (2014) who reported a substantial negative relationship between age and active participation in economic activities such as investing. However, finding is at odds with Edelman (2015) who concluded that the advancement in age did not deter individuals from undertaking important economic decisions such as investments.

The present study found that mixed empirical results were obtained from the two countries with regard to the influence of gender on mobile money adoption. In Zimbabwe, gender had a significant negative effect on adoption of the financial innovation. On the other hand, gender had a significant positive influence on mobile money adoption in South Africa. Findings from Zimbabwe thus differed from existing literature (Van Hove and Dubus, 2019; Demirgüç-Kunt et al., 2018; Biscaye et al., 2017; FinMark Trust, 2016) in that the women in Zimbabwe were more likely to adopt financial innovations than men. On the other hand, the results from South Africa corroborate existing studies that found that men were more likely to adopt mobile financial technology than women. The findings from both countries differed from those of Khan, Akter and Akter (2017), Andersen et al., (2008) and Ramdhony and Munien (2013), however, all of whom noted that there was no difference in mobile financial technology between males and females. This anomalous result emerging from Zimbabwe could possibly be explained by the fact that there more women than men in the country's adult population (FinMark Trust, 2014). As a result, from sheer necessity, women in Zimbabwe were obliged to adopt mobile money technology quickly in order to have access to an instantaneous, safe, cost effective and convenient means to receive remittances.

In line with the literature, Table 7.1 displays mixed results on the effect of marital status on mobile money technology adoption. In Zimbabwe, marital status had a negative but insignificant impact on adoption; that is, generally, the "other" marital category (married, divorced, separated, widowed) were more likely to take up mobile money services than the single. A possible explanation for this outcome may be the need by married individuals to have a safe and convenient means of receiving funds from spouses living elsewhere in the country and in the diaspora. The result in Zimbabwe was consistent with Christiansen et al. (2015), who found that marriage increased the likelihood of financial services and or products' take-up. On the other hand, marital status had a positive but insignificant influence on mobile money adoption in South Africa. Thus, generally, those who were single were more likely to adopt the mobile financial innovation than the "other" marital category. The result in South Africa is similar to findings by Chattopadhyay and Dasgupta (2015), Arano, Parker and Terry (2010), who found that married investors were more risk averse than the single.

The results in Table 7.1 show that in South Africa, employment status had a positive and statistically significant influence on mobile money adoption. Therefore, the employed were more likely to adopt mobile money technology than the unemployed. An explanation for this outcome could be that the use of the mobile money platform is tied to inherent transaction costs, which only the employed can afford to pay as they have regular income sources, in contrast to the unemployed. The outcome thus confirms findings from earlier studies (Chattopadhyay and Dasgupta, 2015; Jain and Mandot, 2012) who found that employed individuals had higher financial risk tolerance than the unemployed owing to their regular income inflows. The result is however in contrast to findings by FinMark Trust (2016), who note that in Southern Africa, unemployed adults had higher levels of mobile money adoption than the employed.

The present study found that personal monthly income had a positive and statistically significant impact on mobile money technology adoption in South Africa. This result implied that individuals with a monthly income stream were more likely to take up mobile money services than those without because they had the capacity to meet the transaction costs. This finding is similar to those of other studies (FinMark Trust, 2016; Murendo et al., 2015a; 2015b; Lasserre, 2015), which established that income was positively significant in influencing mobile money adoption. However, the finding is at odds with the findings of Faff et al. (2008), who noted that income had an adverse impact on financial-decision making.

Household location had a significant negative effect on mobile money technology adoption in Zimbabwe. This result suggests that individuals residing in the rural areas were more likely to adopt the financial innovation than their urban counterparts. This result therefore differs from those of GSMA (2014) and Lwanga and Adong (2016) who are of the view that urbanites are more likely to adopt mobile money than the rural population. These findings are also in contrast to results from Tanzania by Intermedia (2013), who reported higher mobile financial services' adoption rates in the urban areas than in rural areas. A possible reason for such an outcome is the dispersion of population in the country; 65% of the Zimbabwean adult population, the majority of whom are women reside in rural areas. The rural population segment engages in subsistence farming and informal mining activities but is heavily reliant on remittances from family members in urban areas and in the diaspora. (FinMark Trust, 2014). Informal means of remittances are often risky and expensive. Moreover, formal bank ownership is beyond the reach of many because of the high account opening, monthly maintenance and transaction fees, strict know-your-customer bank requirements and the poor physical bank branch presence in the remote peripheries (RBZ, 2016; FinMark Trust, 2016). Hence, the dire need for a safe and affordable formal means of remittance, matched by an extensive mobile money agent distribution throughout the countryside promotes mobile money adoption in rural areas.

The present study found that in Zimbabwe, bank account ownership had a significant negative impact on mobile money adoption. Hence, the unbanked were more likely to use mobile money technology when compared to the banked. This finding corroborates results from a study conducted by FinMark Trust (2016) which reported that bank account ownership is inversely related to mobile money account adoption in Southern Africa. Banked individuals are already financially included, and thus have little impetus to adopt mobile money technology. If banked individuals adopt the financial technology, it is not out of a necessity – rather, it is an additional financial service. On the other hand, the unbanked adopt mobile money services as their only means of accessing rudimentary formal financial services.

7.3 CONTRIBUTION TO THE BODY OF KNOWLEDGE

Empirical studies on mobile money adoption have reported mainly on the influence of socio-economic and other household contextual variables such as gender, marital status, age, income, education, perceived risk, costs, perceived usefulness and social influence (Van Hove and Dubus, 2019; Biscaye et al., 2016; FinMark Trust, 2016; Donovan, 2012; Ramdhony an Munien, 2013; Marumbwa and Mutsikiwa, 2013; Intermedia, 2013). However, despite acknowledging the role of social influence, these studies have failed to investigate how information on mobile money is disseminated through online social networks. The social influence effects that were considered by the above mentioned studies do not clearly demonstrate the mechanisms through which social networks impact on mobile money adoption. The present study departs from such an approach by exploring the relationship between social networking and mobile money adoption decisions.

The study also contributes to the body of knowledge by focusing on a specific type of social networking effect in the form of social media. A few closely related empirical studies (Murendo et al., 2015a; 2015b, Kikulwe et al., 2014; Matsumoto and Munyegera, 2014; Lasserre, 2015; Fafchamps, 2017) have investigated the influence of social networking on mobile money adoption. However, these studies were narrowly focused on offline neighbourhood effects, physical contact, cell phone calls and text messages. As a result, information on mobile money technology is limited to an individual's social network. The current study diverges from this perspective by examining how mobile money adoption is influenced by social media - a present-day key communication channel offering immediacy, a wide reach, cost effectiveness and feedback of information relayed.

In addition, emergent empirical evidence indicates that the use of social media has a significant positive influence on financial behaviour such as purchasing, savings and crowdfunding campaign success (Barhemmati and Ahmad, 2015; Jashari and Rrustemi, 2017; Ammann and Schaub, 2016; Nyagucha, 2017; Qin, 2012; Kaustia and Knüpfer, 2012; Makina, 2017). However, from the literature that has been reviewed by this author, no empirical studies have to date focused specifically on the impact of social media on mobile money technology adoption. The present study fills this gap by revealing the social media-mobile money adoption nexus. From the results of the study, the use of social media has been shown to have a positive and significant influence on mobile money adoption, thereby providing an innovative avenue for reducing financial exclusion that is currently prevalent in developing economies worldwide.

Furthermore, the current study notes that all closely related empirical studies on social networking and mobile money adoption originate exclusively from East Africa, and all, with the exception of Lasserre (2015), were focused on the adult rural population. However, such a geographical bias limits the generalisation of results obtained with respect to: (1) mobile money adoption in the urban localities within East Africa and (2) the other economic regions in Sub-Saharan Africa. The current study fills this gap by investigating mobile money adoption in both the rural and the urban geographical divides in the SADC region. A focus on both types of geographical areas allows for an intra-country comparison of the social media-mobile money adoption nexus, and in response, location-specific pro-adoption policies can be implemented.

In the same vein, a review of closely-related literature undertaken by the author showed that in all the studies, researchers focused on a single country. However, such an approach prevents a comparison of mobile money adoption between countries. The present study adds to the body of knowledge by providing empirical comparative evidence on mobile money adoption from South Africa and Zimbabwe - two economies with remarkable differences in internet penetration, use of social media and financial inclusion. The use of a comparative approach therefore edifies understanding of mobile money adoption drivers across different economies. The use of social media was shown to have had a significant positive impact on mobile money adoption in both countries. However, the comparison of the two countries' results revealed that a higher internet penetration and use of social media rates does not result in high mobile money adoption, as was reported for South Africa. Thus, the use of social media was found to be more effective in Zimbabwe than in South Africa because it has a transformative impact on the financial inclusion landscape in the former.

The current study also avoided investigating the effect of social media on mobile money adoption in the two countries in isolation. It adds to the body of knowledge by showing the effect of the interaction of the social media use and mobile money adoption on the overall extent of mobile money technology adoption. Results of the study revealed that the interaction term significantly increased overall mobile money adoption levels in South Africa and Zimbabwe when compared to the use of social media alone. In addition, a greater amount of mobile money adoption was reported in the latter than the former as shown by the Nagelkerke R^2, the Hosmer and Lemeshow test and Wald test statistics in the Model 2 Block 1 results output for the two countries.

Furthermore, prior closely-related studies have employed either the binary logistic or the binary probit regression model to estimate the influence of social networks on mobile money adoption. The present study on the other hand diverges from such an approach by estimating both models within a study to check for robustness of the results obtained. The use of both binary model estimations allows us to determine whether findings are sensitive to changes in the methodological approach. Consistent with literature, findings from the present study proved that despite differences in scaling, the estimators in the binary logistic and binary probit models led to the same results for both countries (Fenella, 2016; Lewbel et al., 2012; Verbeek, 2004; Park, 2009; Fernando, 2011; Patnaik and Sharma, 2013).

7.4 CONCLUSION

The current study concluded that the use of social media had a significant positive effect on the adoption of mobile money technology, as evidenced by the results from Zimbabwe and South Africa. Furthermore, a high internet and social media penetration rate does not necessarily result in a high mobile money adoption rate, as demonstrated by the case of South Africa. In addition, the present study found that the mere availability of mobile money services in a country does not automatically result in high adoption rates, as was yet again the case in South Africa. Instead, the availability of mobile money services must be matched by demand - it must meet a real need, as is the case in Zimbabwe where 31% of the adult population are financially excluded (FinMark Trust, 2014), and in dire need of rudimentary financial services such as savings, insurance, payments and credit. Mobile money technology does not have a transformative effect in a country with high bank account penetration, as revealed by the findings from the South African data. The current study further determined that the interaction term (use of social media × mobile money adoption) positively impacted on mobile money technology adoption, as substantiated by a significant increase in the Nagelkerke R^2 statistic in South Africa and in Zimbabwe. Apart from the use of social media and the interaction term, there were other determinants of the adoption of mobile money technology. The current study established that while employment and personal monthly income significantly and positively affected adoption of mobile money services, age, household location and bank account ownership had a significant negative influence.

7.5 LIMITATIONS OF THE STUDY

In determining the effect of the use of social media on mobile money adoption, the present study made use of secondary data, and as a result, some constraints were encountered.

The first limitation emanated from the unavailability of secondary data for the use of certain social media platforms by respondents in Zimbabwe (for example Facebook, Twitter, Instagram) with which to compare use in South Africa. As a result, the scope of the measure of social media usage in the former was restricted. In order to manage the problem and allow for comparisons between the two countries, the researcher was forced to accept the use of any one social networking platform as a succinct proxy for use of social media.

The second limitation emerged from the nature of the data collection method, a cross-sectional survey. Despite being a generally quick, easy and cost effective means of data collection, cross-sectional survey data lacks the richness provided by longitudinal surveys such as trends observed in the same respondents (Sedgwick, 2014). As a result, the estimation model employed in the present study was static: it suffered from a lack of dynamism arising from changes observed over time. The binary logistic model therefore does not reveal the sequential association between variables and an outcome, and thus, only an association and not absolute causation can be inferred from a cross sectional study. Analysis of the use of social media-mobile money adoption nexus using data from longitudinal surveys would have provided a deeper insight. In an effort to circumvent the challenge, the researcher opted to investigate the link between the use of social media and mobile money adoption at a given point in time, given that it was a novel study and given the absence of subsequent survey data sets on South Africa and Zimbabwe from FinMark Trust.

The third constraint was that currently there is no literature that focuses specifically on the link between the use of social media and the adoption of mobile money technology. The lack of specialised theory or literature on the subject of this study made it difficult to interpret the results on the use of social media-mobile money adoption nexus. In order to address this, the present study made reference to emergent, closely related literature on (1) offline social network effects on mobile money adoption predominantly from East Africa, and (2) social media and general financial behaviour such as purchasing, investing, savings and crowdfunding campaign success. The closely related literature was used to understand and interpret the results of the effect of use of social media on mobile money adoption in South Africa and Zimbabwe.

7.6 RECOMMENDATIONS OF THE STUDY

The implication of the findings is that mobile money services providers, governments and other relevant stakeholders in developing economies should collectively design and implement policies and programmes that increase internet and mobile phone penetration rates, social media usage, and mobile money adoption in order to achieve significant gains in the financial inclusion drive.

The current study demonstrated that the use of social media positively influences mobile money technology adoption. It is against this backdrop that the researcher recommends that mobile network operators should continually invest in telecommunications infrastructure so as to improve internet connectivity across countries, particularly in the rural peripheries. This is vital if they wish to increase their share of the mobile money market and enjoy adoption-related advantages such as increased volumes of transaction fees which overtime translate into larger revenue sources.

Furthermore, mobile money service providers could increase their social media presence through aggressive social media marketing initiatives across all online social networking platforms patronised by internet users in a country. The current study showed that the interaction of social media use and mobile money adoption significantly increased the overall adoption rates. Accordingly, service providers would benefit from incentivising current adopters who also use social media (for example by providing free data, making reward deposits into their mobile money accounts) to reach out to their non-adopter network members and encourage adoption. Leveraging on incentivised adopters therefore enhances service providers' presence on social media platforms, leading to increased adoption of mobile money technology.

Furthermore, the present study recommends that mobile network operators leverage on economies of scale from current high cell phone penetration rates in developing countries and reduce internet data access costs. This would in turn allow more people to access the internet, and thus to use social media platforms more frequently, to acquire more mobile money related information, and to spread it in real-time through likes, shares, forwards or tweets to others. The spread of information could go viral, leading to increased mobile money adoption through the influence of social media.

The present study also found that in Zimbabwe, women were more likely to adopt mobile money technology than men, while in South Africa men were more likely. In response to this outcome, the researcher recommends intensified mobile money literacy campaigns with a specific focus on women be undertaken in developing countries. Improved understanding of mobile money technology among women in developing countries would encourage further adoption.

The current study found that the current liquidity crisis experienced in Zimbabwe since May 2016 had resulted in mobile money platforms being adopted as an alternative payment mode (FinMark Trust, 2016). As a result, it is recommended that mobile money service providers offer a wider spectrum of services in order to further increase adoption. In addition to payments, remittances and basic insurance, service providers could provide (1) an incentivised savings scheme that is tied to the prevailing market interest rate, and (2) micro and small business credit/loan facilities (in addition to the current voice airtime and data advances), which are tied to an individual’s deposits. A wider range of services would also dissuade many of the currently financially excluded from seeking out costly informal services that merely perpetuate the cycle of poverty. Financial inclusion through making credit facilities available to those in peripheral rural areas would encourage entrepreneurial start-ups, and the ensuing growth would feed into a country’s economic development.

It was observed in the present study that regulatory challenges were reported as a hindrance to mobile money adoption in South Africa (FinMark Trust, 2017). Currently, mobile money service providers must follow the prescriptions set for the banking sector, yet mobile money platform operations are technically different from conventional banking. The effect of these regulatory barriers stifles mobile money service providers' ability to launch cost competitive, innovative, acceptable and interoperable mobile money services. Against this background, it is recommended that a more permissive regulatory framework that specifically addresses mobile money technology be implemented in South Africa. Introduction of more tolerant regulations would minimise barriers to entry, leading to increased adoption of this financial innovation.

FinMark Trust (2017) found that agent challenges were some of the causes of the current low adoption of mobile money services in South Africa. In response, the present study recommends that mobile money services providers build their own mobile money agent network and intensify support for agents through improved information to relay to users and increased cash floats. Expanded agent networks and support would ensure undisrupted mobile money service delivery to customers and encourage more adoption.

7.7 SUGGESTIONS FOR FURTHER STUDY

The current study investigated the effect of social media on mobile money adoption, with a specific focus on South Africa and Zimbabwe. It would be interesting to apply the same concept to other countries within the SADC region, as well as other regional blocs from developing markets (for example East Africa, which successfully pioneered mobile money services), and also the developed countries. Findings from such studies would be useful in determining the impact of the use of social media (and the most effective social media platforms) on mobile money technology adoption.

Subject to data availability, it is suggested that further studies using variables that were excluded from the present one such as costs, perceived risk, religion, and locus of control among others be undertaken. Such studies would be valuable in explaining a greater proportion of the total variance in mobile money adoption.

In addition, the use of longitudinal survey data will allow for a more nuanced understanding of the link between the use of social media and mobile money technology adoption. It is also important to subject the FinScope consumer survey South Africa 2015 and Zimbabwe 2014 data sets to a different estimation method such as linear probability modelling to add to the robustness of this study.

BIBLIOGRAPHY

Aboelmaged, M. and Gebba, T. (2013). Mobile banking adoption: An examination of the TAM and TPB model. *International Journal of Business Research and Development*, Vol. 2(1): 35-50.

Abu-Shanab, E., Pearson, J. and Setterstrom, A. (2010). Internet banking and customers' acceptance in Jordan: The unified model's perspective. *Communications of the Association for Information Systems*, Vol. 26(23): 493-525.

African Development Bank (2013). Financial inclusion in Africa Report. AfDB.

Agarwal, S., Driscoll, J. C., Gabaix, X., and Laibson, D. (2009). The age of reason: Financial decisions over the life-cycle and implications for regulation. *Brookings Papers on Economic Activity.*

Agresti A., 2007. *Introduction to Categorical Data Analysis*. John Wiley & Sons, Hoboken: New Jersey.

Ahmed, I. S. Y. (2017). Determinants of continuance intention to use mobile money transfer: an integrated model. *Journal of Internet Banking and Commerce Journal of Internet Banking and Commerce*, Vol. 22(7): 1-24.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, Vol. 50(2): 179–211.

Ajzen, I. (2002). Perceived behavioural control, self-efficacy, locus of control and the theory of planned behaviour. *Journal of Applied Social Psychology*, Vol. 32(4): 665-683.

Ajzen, I. and Fishbein, M. (1975). *Belief, attitude, intention and behavior: An introduction to theory and research*. 1st Edition. Addison-Wesley.

Ajzen, I. and Fishbein, M. (1980). *Understanding attitudes and predicting social behavior.* Prentice-Hall: Englewood Cliffs, New Jersey:

Akar, E. (2010). Sosyal Medya Pazarlaması: Sosyal Webde Pazarlama Stratejileri, Efil Yayınevi, Ankara.

Aker, J. C., and Wilson, K. (2013). Can mobile money be used to promote savings? Evidence from preliminary research in Northern Ghana. *Swift Institute Working Paper* No. 2012-003.

Aker, J., Boumnijel, R., McClelland, A. and Tierney, N. (2011). Zap It to Me: The Short-Term Impacts of a Mobile Cash Transfer Program. *Center for Global Development,* Working paper 268, Washington DC.

Alatas, V., Banerjee, A., Chandrasekhar, A. G., Hanna, R. and Olken, B. A. (2016). Network structure and the aggregation of information: theory and evidence from Indonesia. *American Economic Review,* Vol. 106(7): 1663–1704.

Alex, K. and Amos, A. (2014). The role of financial literacy in promoting children and youth savings accounts: A case of commercial banks in Kenya. *Research Journal of Finance and Accounting*, Vol. 5(11): 106-110.

Al-Fahim, N. H. (2013). An exploratory study of factors affecting the internet banking adoption: A quantitative study among postgraduate students. *Global Journal of Management and Business Research Finance*, Vol. 13(8): 23-32.

Al-Gahtani, S. S., Hubona, G. S. and Wang, J. (2007). Information technology (It) in Saudi Arabia: Culture and the acceptance and use of it. *Information and Management,* Vol. 44(8) 681-691.

Al-Ghamdi A. S. (2001). *Using logistic regression to estimate the influence of accident factors on accident severity*. King Saud University, Pergamon.

Ali, A. Y. S. and Dhaha, I. S. Y. (2013). Factors influencing mobile money transfer adoption among Somali students. *International Journal of Business Economic Law* Vol. 3(1): 1-9.

Al-Jabri, I. M. and Sohail, M. S. (2012). Mobile banking adoption: Application of diffusion of innovation theory. *Journal of Electronic Commerce Research*, Vol. 13(4): 379-391.

Al-Majali, M. and Mat, N. K. (2011). Modeling the antecedents of internet banking service adoption (IBSA) in Jordan: A Structural Equation Modeling (SEM) approach. *Journal of Internet Banking and Commerce*, Vol. 16(1)1-15.

Alomary, A. and Woollard, J. (2015). How is technology accepted by users? A review of technology acceptance models and theories. *Proceedings of: IRES 17th International Conference, London, 21st November 2015.*

Alsamydai, M. J., Yassen, S. G., Alnaimi, H. M., Dajani, D. M. and Al-Qirem, I. A. (2014). The factors influencing customer usage of mobile banking services in Jordan. *International Journal of Business Management and Research*, Vol. 4(2): 63-78.

Al-Tarawneh J. M. (2016). Factors influencing the adoption of mobile banking services in Jordan from the perspective of customers: Overview and pilot study. *International Journal of Scientific and Research Publications*, Vol. 6(9): 207-213.

Ammann, M. and Schaub, N. (2016). Social Interaction and Investing: Evidence from an online social trading network. *St. Gallen, Switzerland: Swiss Institute of Banking and Finance,* University of St. Gallen.

Ammar, A. and Ahmed, E. M. (2016). Factors influencing Sudanese microfinance intention to adopt mobile banking. *Cogent Business and Management,* Vol. 3(1):1-20.

Andersen, S., Harrison, G. W., Lau, M. I. and Rutström, E. E. (2008). Lost in state space: Are preferences stable? *International Economic Review*, Vol. 49(3): 1091-1112.

Angelucci, M., De Giorgi, G. and Rasul, I. (2017). Resource pooling within family networks: Insurance and investment. IFS Working Paper W18/17.

Arano, K., Parker, C. and Terry, R. L. (2010). Gender-based risk aversion and retirement asset allocation. *Economic Inquiry*, Vol. 48(1): 147-155.

Arifin, A. Z. (2017). The influence of financial knowledge, control and income on individual financial behavior. *European Research Studies Journal*, Vol. 20(3A): 635-648.

Aron, J. (2017). Leapfrogging: A survey of the nature and economic implications of mobile money. *CSAE Working Paper* No. WPS/2017-02.

Ayodele, A. E. (2012). *A critical analysis of diffusion of innovation theory*. [Online]. Available at https://www.wordpress.com [Accessed 28 February 2017].

Badinenko, O., Barasinska, N. and Schafer, D. (2011). Risk attitudes and investment decisions across European countries – Are women more conservative investors than men? *Discussion Papers (928), German Institute for Economic Research.*

Bagozzi, R. P. (2007). The legacy of the technology acceptance model and a proposal for a paradigm shift. *Journal of the Association of Information Systems*, Vol. 8(4): 244-254.

Bains, W., Wooder, S. and Guzman, D. R. M. (2014). Funding Biotech start-ups in a Post-VC World. *Journal of Commercial Biotechnology*, Vol. 20(1): 10-27.

Baker, H. K. and Ricciardi, V. (2014). *Investor Behavior: The psychology of financial planning and investing*. (Eds.), Hoboken, New Jersey: John Wiley and Sons.

Bandura, A. (1986) *Social foundations of thought and action: A social cognitive theory*. Englewood Cliffs, New Jersey: Prentice Hall.

Banerjee, A., Chandrasekhar, A. G., Duflo, E. and Jackson, M. O. (2013). The diffusion of microfinance. *Science,* Vol. 341(6144): 363-371.

Barhemmati, N. and Ahmad, A. (2015). Effects of social network marketing (SNM) on consumer purchase behavior through customer engagement. *Journal of Advanced Management Science*, Vol. 3(4): 307-311.

Batista C, Vicente P (2013) Introducing mobile money in rural Mozambique: Evidence from a field experiment. *Working Paper 1301, Nova Africa Center for Business and Economic Development, Nova University of Lisbon.*

Beaman. L., BenYishay, A., Magruder, J. and Mobarak, A. M. (2018). Can network theory-based targeting increase technology adoption? *National Bureau of Economic Research,* Working Paper No. 24912.

Beier, M. and Wagner, K. (2015). Crowdfunding success: A perspective from social media and e- commerce. *Proceedings of the Thirty-sixth International Conference on Information Systems, Fort Worth 2015*.

Berthon, P. R., Pitt, L. F., Plangger, K. and Shapiro, D. (2012). Marketing meets Web 2.0, social media, creative consumers: Implications for international marketing strategy. *Business Horizons,* Vol. 55(3): 261-271.

Beshears, J., Choi, J. J., Laibson, D., Madrian, B. C. and Milkman, K. L. (2015). The effect of providing peer information on retirement savings decisions. *Journal of Finance*, Vol. 70(3): 1161-1201.

Biscaye, P., Fowle, M., Knauer, J., O'Brien-Carelli, C. Orlebeke, A. Reynolds, T. and Anderson, L. C. (2017). Digital financial services and gender: An analysis of correlates of awareness, adoption, and use. *EVANS SCHOOL POLICY ANALYSIS AND RESEARCH (EPAR).*

Blumenstock J, Eagle N. and Fafchamps, M. (2014). Risk and reciprocity over the mobile phone network: evidence from Rwanda. *CSAE Working Paper Series 2011 - 19, Centre for the Study of African Economies, University of Oxford.*

Blumenstock, J. E., Cadamuro, G. and On, R. (2015). Predicting Poverty and Wealth from Mobile Phone Metadata. *Science* 350 (6264): 1073–76.

Borgatti, S. P., Mehra, A., Brass, D. J. and Labianca, G. (2009). Network analysis in the social sciences. *Sciences,* Vol. 323(5916): 892-895.

Bourdieu, P. (1977). *Outline of a theory of practice Nice R, translator*. Cambridge: Cambridge University Press.

Bourdieu, P. and Wacquant, L. J. D. (1992). *An invitation to reflexive sociology.* Chicago: The University of Chicago Press.

Boyd, D. (2006). Friends, Friendsters, and MySpace Top 8: Writing community into being on social network sites [Online]. Available at:https://firstmonday.org/ojs/index.php/fm/article/view/1418/1336.[accessed 15 November 2017].

Breza, E. and Chandrasekhar, A. (2015). Social networks, reputation, and commitment: Evidence from a savings monitors experiment. *National Bureau of Economic Research Working Paper.*

Brown, D. and Hayes, N. (2008). *Influence of marketing: Who really influences your customers?* Oxford: Butterworth-Heinemann.

Brown, R. (2009). *Public Relations and the Social Web: How to Use Social Media and Web 2.0 in Communications*. New Jersey: Kogan Page Publishers.

Bryman, A. and Bell, E. (2011). *Business research methods*. 3rd Edition, New York: Oxford University Press Inc.

Bursztyn, L., Ederer, F., Ferman, B. Yuchtman, N. (2014). Understanding peer effects in financial decisions: Evidence from a field experiment. *Econometrica,* Vol. 82(4): 1273–1301.

Burt, R. S. (1987). Social contagion and innovation: Cohesion versus structural equivalence. *American Journal of Sociology*, Vol. 92(6): 1287–1335.

Cai, J., A. De Janvry, and E. Sadoulet (2015). Social networks and the decision to insure. *American Economic Journal: Applied Economics*, Vol. 7(2): 81–108.

Camner, G., and E. Sjöblom. (2009). Can the success of M-Pesa be repeated? A review of implementations in Kenya and Tanzania. *Valuable Bits Note*.

Carrigan M. (2016). *Social media for academics*. London: SAGE Publications Ltd.

Cenfri (2013). [Online]. Available at: www.cenfri.org/publications/measurement-framework-note [Accessed 14 March 2019].

Cenfri (2016). Homefield advantage- Learning from the popularity of local financial services providers. *MAP Global Insight Series*: Note 3.

Cenfri (2017). [Online]. Available at: https//www.centerforfinancialinclusion.org/fortycountriesandstillcountingcommittedtothemayadeclaration [Accessed 26 March 2019].

Chang, C. C., Tseng, K. H., Liang, C. and Yan, C. F. (2013). The influence of perceived convenience and curiosity on continuance intention in mobile English learning for high school students using PDAs. *Technology, Pedagogy and Education*, Vol. 22(3): 373-386.

Chattopadhyay, S. and Dasgupta, R. (2015). Demographic and socioeconomic impact on risk attitudes of the Indian investors – An empirical study. *Asian Economic and Financial Review*, Vol. 5(4): 601-623.

Chemingui, H. and lallouna, H. B. (2013). Resistance, motivations, trust and intention to use mobile financial services. *International Journal of Bank Marketing,* Vol. 31(7): 574-592.

Chen, S., and Li, S. (2011). Recent related research in technology acceptance model: A literature review. *Australian Journal of Business and Management Research,* Vol. 1(9): 124–127.

Chile, P. (2017). Some of the disadvantages of the diffusion of innovation theory. [Online]. Available at:http//bifluent.com/info-8633492-disadvantages-using-diffusion-theory.html [Accessed 23 January 2019].

Chitungo, S. K. and Munongo, S. (2013). Extending the technology acceptance model to mobile banking adoption in rural Zimbabwe. *Journal of Business Administration and Education*, Vol. 3(1): 51-79.

Choi, S., Kariv, S., Muller, W., and Silverman, D. (2014). Who is (more) rational? *American Economic Review*, Vol. 104(6): 1518-1550.

Christakis, N. A. and Fowler, J. H. (2013). Social contagion theory: Examining Dynamic Social Networks and Human Behavior. *Statistics in Medicine,* Vol. 32(4): 556-577.

Christiansen, C. Joensen, J. S. and Rangvid, J. (2015). Understanding the effects of marriage and divorce on financial investments: the role of background risk sharing. *Economic Inquiry*, Vol. 53(1): 431-447.

Chuang, Y. (2014). Self-control or social control? Peer effects on temptation consumption. *Proceedings of the Annual Meeting, 4-6 August 2013, Washington, DC.*

Cole, S., Zia, B., Abel, M., Crowley, L., Pauliac, C. S. and Postal, V. (2014). Evaluation of Old Mutual's on the money program: Financial literacy in South Africa.

In Lundberg, M. and Mulaj, F. (Eds.): *Enhancing financial capability and behavior in low and middle-income countries.* The World Bank, Washington DC: 151-494.

Communications Commission of Kenya. (2013). *Quarterly Report*, January 2013, Nairobi, Kenya.

Cosma, S. and Pattarin, F. (2012). Psychological determinants of consumer credit: the role of attitudes. *Review of Behavioural Finance*, Vol. *4*(2): 113-129.

Cox, D. R. and Snell, E. J. (1989). *Analysis of binary data*. 2nd Edition, London: Chapman and Hall/CRC.

Criddle, E. (2006). Financial literacy: Goals and values, not just numbers. *Alliance* 34.

Cudjoe, A.G., Anim, P.A. and Nyanyofio, J.G.N.T. (2015). "Determinants of mobile banking adoption in the Ghanaian banking industry: A case of Access Bank Ghana Limited". *Journal of Computer and Communications*, Vol. 3 (1): 1-19.

Cull, R., Ehrbeck, T. and Holle, N. (2014). Financial inclusion and development: Recent impact evidence. *Consultative Group to Assist the Poor*, Focus Note 9/2014.

Cunningham, C. M. (2013). *Social networking and impression management: Self-presentation in the digital age.* Eds. Lanham: Rowman and Littlefield Publishing Group Inc.

Czerwonka, M. (2014). The Influence of religion on socially responsible investing. *Journal of Religion and Business Ethics*, Vol. 3, Article 21: 1-10.

Dass, R. and Pal, S. (2011). Exploring the factors affecting the adoption of mobile financial services among the rural under-banked. *Indian Institute of Management Ahmedabad.*

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, Vol. 13(3): 319– 340.

Davis, F. D., Bagozzi, R. P. and Warshaw, P. R. (1992). Extrinsic and intrinsic motivation to use computers in the workplace. *Journal of Applied Social Psychology,* Vol. 22(14): 1111-1132.

Dayioglu, Y. and Gumus, B. F. (2015). An analysis on the socio-economic and demographic factors that have an effect on the risk taking preferences of personal investors. *International Journal of Economics and Financial Issues*, Vol. 5 (1): 136-147.

De Silva, H., Ratnadiwakara, D. and Zainudeen, A. (2011). Social influence in mobile phone adoption: Evidence from the bottom of the pyramid in emerging Asia. *ISC Annenberg School for Communication and Journalism*, Vol. 7(3): 1-18.

Demirgüç-Kunt, A., Klapper, L., Singer, D., Ansar, S. and Hess, J. (2018). The Global Findex Database 2017: Measuring financial inclusion and the Fintech revolution. Washington, DC: World Bank.

Demombynes, G. and Thegeya, A. (2012, March). Kenya's mobile revolution and the promise of mobile savings. *World Bank Policy Research Working Paper, No. 5988*. Washington, DC.

Di Castri, S. (2013). Enabling Mobile Money Policies in Sri Lanka. The Rise of eZ Cash. *GSMA, Mobile Money for the Unbanked Paper 15*.

Di Falco, S. and Bulte, E. (2013). The impact of kinship networks on the adoption of risk-mitigating strategies in Ethiopia. *World Development,* Vol. 43(2): 100–110.

Donovan, K. 2012. Mobile Money for Financial Inclusion. *Information and Communications for Development*, Vol. 61(1): 61–73.

Dupas, P. and J. Robinson (2013a). Savings constraints and microenterprise development: Evidence from a field experiment in Kenya. *American Economic Journal: Applied Economics*, Vol. 5(1): 163–92.

Easley, D. and Kleinberg, J. (2010). *Networks, crowds and markets: Reasoning about a highly connected world.* London, Cambridge University Press.

Edelman, R. (2015). How does aging affect your financial decisions? Inside Personal Finance. [Online]. Available: https://www.edelmanfinancial.com/education-center/articles/how-does-aging-affect-yourfinancial-decisions [accessed 15 September 2017].

Edwards, R. (2015). *An investigation into the use of social networking sites by young people and the perceived benefits.* Hamburg: Anchor Academic Publishing.

Ehrbeck, T., Pickens, M. and Tarazi, M. (2012). Financially inclusive ecosystems: The roles of government today. *Consultative Group to Assist the Poor (CGAP) report.*

Eldridge, R. (2016). How Social Media is Shaping Financial Services. [Online]. Available at: https://www.huffpost.com/entry/how-social-media-is-shapi_b_9043918 [Accessed 31 October 2018].

Ellison, N. B., Steinfield, C. and Lampe, C. (2007). The benefits of Facebook ‘‘friends”: Social capital and college students’ use of online social network sites. *Journal of Computer Mediated Communication,* Vol. 12(4): 1143–1168.

European Computer Driving Licence Foundation (ECDL). (2009). *Digital literacy report.*

Evans L. (2015). *Locative social media: Place in the digital age.* London: Palgrave Macmillan.

Fafchamps, M., Söderbom, M. and van den Boogaart, M. (2017). Adoption with social learning and network externalities. *National Bureau of Economic Research Working Paper*.

Faff, R., D. Mulino and D. Chai, (2008). On the linkage between financial risk tolerance and risk aversion. *Journal of Financial Research*, Vol. 31(1): 1-23.

Fernando, R. (2011). Logit, Probit and Tobit: models for categorical and limited dependent variables. Paper presented at PLCS/RDC Statistics and Data Series at Western conference.

Fenella, C. (2016). Regressions with binary dependent variables. *GSI Econ 140 Spring Notes*, Section 10: 1-7.

FinMark Trust (2014). *FinScope Consumer Survey Zimbabwe 2014*. FinMark Trust, Johannesburg.

FinMark Trust (2015). *FinScope South Africa 2015*. FinMark Trust, Johannesburg.

FinMark Trust (2016). The role of mobile money in financial inclusion in the SADC region. Evidence using FinScope Surveys. *FinMark Trust policy research paper No.03/2016.*

FinMark Trust (2016). *Zimbabwe financial inclusion country report*. FinMark Trust, Johannesburg.

FinMark Trust (2017). *Research report on mobile money in South Africa*. FinMark Trust, Johannesburg.

Fox, H. (2010). Logit and probit models. *York Spida Notes*.

Gamble, K. J., Boyle, P. A., Yu, L., and Bennett, D.A. (2015). How does aging affect financial decision making? *Center for Retirement Research*, Vol. 15(1): 1-7.

Garrido-Morreno, A. and Lockett, N. J. (2016). Social media use in European hotels: Benefits and main challenges. *Tourism and Management Studies,* Vol. 12(1): 172-179.

Giné, X., Karlan, D. and Ngatia, M. (2014). Social network, financial literacy and index insurance: evidences from a randomized experiment in Kenya. In Mattias-Lundberg, M. and Mulaj, F. (Eds), E*nhancing financial capability and behavior in low and middle-income countries*: The World Bank, Washington DC: 196-208.

Giudici, G., Guerini, M. and Rossi-Lamastra, C. (2013). Why crowdfunding projects can succeed: The Role of proponents' individual and territorial social capital. *Journal of Industrial and Business Economics,* Vol. 40(4): 173-188.

Goffman, E. (1959). *The presentation of self in everyday life*. Bantam Doubleday Dell Publishing Group Inc.: New York.

Gorodnichenko, Y. and Rolland, G. (2011). Understanding the individualism-collectivism cleavage and its effects: Lessons from cultural psychology. *Invited paper at the 16th Congress of the International Economic Association*.

Grable, J. E., Park, J. Y. and. Joo, S. H. (2009). Explaining financial management behavior for Koreans living in the United States. *The Journal of Consumer Affairs*, Vol. 43(1): 80-107.

Granovetter, M. (2005). The impact of social structure on economic outcomes. *Journal of Economic Perspectives*, Vol. 19(1): 33-50.

Granovetter, M. S. (1973). The strength of weak ties. *American Journal of Sociology,* Vol. 78(6): 1360-1380.

Granovetter, M.S. (1983). The strength of weak ties: a network theory revisited. *Sociological Theory*, Vol. 1: 201-233.

Greene, W. (2008). Discrete choice modeling. In Mills, T. and Patterson, K. (Eds.): *The handbook of econometrics*: Vol. 2, Applied Econometrics, Part 4.2., London: Palgrave.

Greene, W. H. (1993). *Econometric analysis*. 2nd Edition. Macmillan: New York.

Greene, W. H. (1997). Econometric Analysis. 3rd Edition. Upper Saddle River, New Jersey: Prentice-Hall

Greene, W. H. (2008). *Econometric analysis*. 6th Edition. Upper Saddle River: Pearson Prentice Hall.

Greene, W. H. (2010). *Testing hypotheses about interaction terms in nonlinear models. Economic Letters,* Vol. 107(2): 291-296.

Greene, W. H. (2012). *Econometric analyses*. 7th Edition. Pearson Education: England.

Gros, C. H. (2012). The influence of social media on consumers during their purchase decision making process and implications for marketers. Masters of Business Studies Dissertation, Dublin Business School.

Groupe Speciale Mobile Association (GSMA) (2015). The mobile economy Sub-Saharan Africa. *GSMA Intelligence*.

Groupe Speciale Mobile Association (GSMA). (2014). The mobile economy 2014. *GSMA Intelligence.*

Groupe Speciale Mobile Association (GSMA). (2015). Building digital societies in Asia: Making commerce smarter. *GSMA Intelligence.*

Groupe Speciale Mobile Association (GSMA). (2016). The mobile economy Sub-Saharan Africa 2015 report. *GSMA Intelligence.*

Groupe Speciale Mobile Association (GSMA). (2017). State of the industry report on mobile money. *GSMA Intelligence.*

Groupe Speciale Mobile Association (GSMA). (2018). The mobile economy Sub-Saharan Africa 2018 report, *GSMA Intelligence.*

Hall, B. H. and Khan, B. (2003). Adoption of new technology. In Jones, Derek C. (ed), *New Economy Handbook*, Amsterdam: Elsevier Science.

Hanafizadeh, P., Behboudi, M., Koshksaray, A. A. and Tabar, M. J .S. (2014). Mobile-banking adoption by Iranian bank clients. *Telematics and Informatics,* Vol. 31(1): 62 –78.

Hansen, D. L., Shneiderman, B. and Smith, M. A. (2011). *Analysing social media networks with NodeXL: Insights from a connected world*. Burlington: Morgan Kaufmann.

Harrell F. E. Jr., (2001). *Regression modeling strategies: With applications to linear models, logistic regression, and survival analysis*. New York: Springer.

Hayta, A. B. (2013). A study on the effects of social media on young consumers' buying behaviours. *European Journal of Research on Education.* Special Issue: Human Resource Management: 65-74.

Heimer, R. Z. (2016). Peer Pressure: Social Interaction and the disposition effect. *Review of Financial Studies*, Vol. 29(11): 3177–3209.

Hess, D. W. (2012). The impact of religiosity on personal financial decisions. *Journal of Religion and Society*, Vol. 14: 1-13.

Hootsuite (2017). Digital in 2017: Southern Africa. [Online]. Available at https://www.slideshare.net/wearesocialsg/digital-in-2017-southern-africa.[Accessed 24 October 2018].

Hosmer D. W. and Lemeshow S. (2000). *Applied logistic regression*. 2nd Edition. New York: John Wiley and Sons.

Hoyer, W. D. and MacInnis, D. J. (2010) *Consumer behavior*. 5th Edition, London: South-Western Cengage Learning.

Hussain, M. A. (2013). A questionnaire approach based on the technology acceptance model for mobile tracking on patient progress applications. *Journal of Computer Science,* Vol. 9(6): 763-770.

IBM Software (2012). Grasping the power of social networking for financial services seizing the opportunity, maintaining regulatory compliance. *A Business White Paper from IBM Software, Enterprise Content Management*: 1-16.

InterMedia (2013). Mobile money in Uganda: Use, barriers and opportunities. The Financial Inclusion Tracker Survey Project. *InterMedia*, Washington, DC.

International Monetary Fund (2016). International Monetary Annual Report.

International Telecommunications Union (ITU). (2015). *Measuring the Information Society Report.*

Jack, W. and Suri, T. (2011). Mobile money: the economics of M-PESA. *National Bureau of Economic Research, Working Paper No.16721*, Cambridge, MA.

Jack, W. and Suri, T. (2014). Risk sharing and transaction costs: evidence from Kenya's mobile money revolution. *American Economic Review*, Vol. 104(1): 183–223.

Jack, W., Ray, A and Suri, T. (2013). Transaction networks: evidence from mobile money in Kenya. *American Economic Review*, Vol. 103(3): 356-361.

Jain, D. and Mandot, N. (2012.) Impact of demographic factors on investment decision of investors in Rajasthan. *Journal of Arts, Science and Commerce*, Vol. 3(2): 81 -92.

Jaradat, M. R. and Al Rabaa, M. S. (2013). Assessing key factors that influence on the acceptance of mobile commerce based on modified UTAUT. *International Journal of Business and Management*, Vol. 8(23): 102-112.

Jashari, F. and Rrustemi, V. (2017). The impact of social media on consumer behaviour- Case study Kosovo. *Journal of Knowledge Management, Economics and Information Technology,* Vol. 7(1): 1-21.

Jenkins, B. (2008). Developing mobile money ecosystems. *International Finance Corporation, World Bank and Harvard Kennedy School of Government*.

Jokonya, O. (2015). Validating technology acceptance model (TAM) during IT adoption in organisations. *Proceedings of the 7th IEEE Conference Cloud Computing Technology and Science, Vancouver, Canada*.

Jokonya, O. (2017). Critical literature review of theory of planned behaviour in the information's systems research. *Proceedings of the 2nd International Conference on Advances in Management Engineering and Information Technology (AMEIT), Shanghai, China.*

Jusilla, A. (2015). Mobile money as an enabler for entrepreneurship: Case Eastern Africa. Entrepreneurship Master's Thesis. Aalto University School of Business, Aalto.

Kahraman, M. (2010). Sosyal Medya 101, Mediacat, 1.Baskı. İstanbul.

Kast, F., Meier, S. and Pomeranz, D. (2012). Under-savers anonymous: Evidence on self-help groups and peer pressure as a savings commitment device. *National Bureau of Economic Research Working Paper.*

Kaustia, M. and Knüpfer, S. (2012). Peer performance and stock market entry. *Journal of Financial Economics*, Vol. 104(2): 321-338.

Kavitha, S. and Bhuvaneswari, R. (2017). Usage of social media among the equity investors with special reference to selected stock broking firms in Coimbatore. *Management Today*, Volume 7(4): 214-221.

Kerkhof, J. (2016). The influence of a social network and social interactions on the success of a crowdfunding campaign. *Proceedings of the 7th IBA Bachelor Thesis Conference, Enschede, Netherlands, July 1st 2016.*

Khalifa, M., Cheng, S. K. N. and Shen, K. N. (2012). Adoption of mobile commerce: A confidence model. *Journal of Computer Information Systems*, Vol. 53(1): 14-22.

Khan, S. N., Akter, M. and Akter, R. (2017). Factors influencing adoption and usage of mobile banking: Bangladesh Experience*. International Journal of Finance and Banking Research*. Vol. 3(1): 1-12.

Khatib, F. (2016). The impact of social media characteristics on purchase decisions. Empirical study of Saudi customers in Aseer Region. *International Journal of Business and Social Science,* Vol. 7(4): 41-50.

Kholilah, N. A. and Iramani, R. (2013). Studi financial management behavior Pada Masyarakat Surabaya. *Journal of Business and Banking,* Vol. 3(1): 69-80.

Kholoud, I. A. (2009). Analyzing the use of UTAUT model in explaining an online behaviour: Internet banking adoption. PhD Thesis, Brunel University, London.

Kiconco, R. I., Rooks, G., Solano, G. and Maztat, U. (2018). A skills perspective on the adoption and use of mobile money services in Uganda. *Information Development,* DOI: 10.1177/0266666918788908.

Kikulwe, E.M., Fischer, E. and Qaim, M. (2014). Mobile money, smallholder farmers and household welfare in Kenya. *PloS one*, 9: 1-13.

Kim, C., Mirusmonov, M. and Lee, I. (2010). An empirical examination of factors influencing the intention to use mobile payment. *Computers in Human Behavior*, Vol. 26(3): 310–322.

Kim, S. H., Jang, S. Y. and Yang, K. H. (2017). Analysis of the determinants of software-as-a-service adoption in small businesses: Risks, benefits, and organizational and environmental factors. *Journal of Small Business Management*, Vol. 55(2): 303-325.

Kind, M. (2014). Microeconometrics. Summer term notes.

Kinnan, C. and Townsend, R. (2012). Kinship and financial networks, formal financial access, and risk reduction. *American Economic Review: Papers and Proceedings*, Vol. 102(3): 289-293.

Kirakosyan, K. (2015). Social Media Usage in Banking Industry and Its Managerial View: Case Study for Mexican Banking System. *Journal of Economic and Social Development*, Vol 2 (1): 34-43.

Kirui, O. K., Okello, J. J. and Nyikal, R. A. (2012). Determinants of use and intensity of mobile phone-based money transfer services in smallholder agriculture: case of Kenya. *Paper prepared for the International Association of Agricultural Economists (IAAE) Triennial Conference, Foz do Iguaçu, Brazil, 18-24 August, 2012*.

Klapper, L. and Singer, D. (2017). The opportunities and challenges of digitizing government-to-person payments*. The World Bank Observer*, Vol. 32(2); 211-226.

Kleinbaum, D. G. and Klein, M. (2010). Logistic regression: A self-learning text. 3rd Edition, London: Springer.

Knudsen, S. (2015). Facebook advertising and your crowdfunding project. [Online]. Available at: http://commandpartners.com/blog/facebook-advertising-and-your-crowdfunding-project [Accessed 6 January 2017]

Koening-Lewis, N., Palmer, A. and Moll, A. (2010). Predicting young consumers' take up of mobile banking services. *International Journal of Bank Marketing*, Vol. 28(5): 410–432.

Korniotis, G. M. and Kumar, A. (2011). Do older investors make better investment decisions? *Review of Economics and Statistics*, Vol. 93(1): 244-265.

Kosavinta, S., Krairit, D. and Khang, D. (2017). Decision making in the pre-development stage of residential development. *Journal of Property Investment and Finance*, Vol. 35(2): 160-183.

Kuchciak, I. (2013). How social media will change the future of banking services. *International Proceedings of Economics Development and Research*, Vol. 65(1): 1-5.

Kutner M. H., Nachtsheim C. J., Neter J. and Li W. (2005). *Applied Linear Statistical Model*. 5th Edition. New York: McGraw-Hill.

Lachs, M. S. and Han, S. D. (2015). Age-associated financial vulnerability: an emerging public health issue. *Annals of Internal Medicine,* Vol. 163(11): 877-878.

Lal, R. and Sachdev, I. (2015). Mobile money services – Design and development for financial inclusion. *Harvard Business School,* Working Paper 15-083.

Langley, D. J., Bijmolt, T. H. A., Ortt, J. R. and Pals, N. (2012). Determinants of social contagion during new product adoption. *Journal of Product Innovation Management*, Vol. 29(4): 623–638.

Lasserre, P .I. P. (2015). Social Networks and Mobile Money Adoption: A quantitative case study in Uganda. Masters Dissertation. Eindhoven University of Technology, Eindhoven.

Lawrence S. M., Gamst G. and Guarino A. J. (2006). *Applied multivariate research: design and interpretation*. London: Sage Publications Inc.

Lema, A. (2017). Factors influencing the adoption of mobile financial services in the unbanked population. *Inkanyiso Journal of Humanities and Social Sciences*, Vol. 9(1): 37-51.

Letamendia, L. N. and Silva, A. C. (2017). Factors influencing saving and investment: Financial literacy, attitudes and trust. *Center for Insurance Research*, Working Paper.

Lewbel, A., Dong, Y. and Yang, T. T. (2012). Comparing features of convenient estimators for binary choice models with endogenous regressors. *Canadian Journal of Economics*, Vol. 45 (1): 809–829.

Livingstone, S. (2008). Taking risky opportunities in youthful content creation: Teenagers' use of social networking sites for intimacy, privacy and self-expression. *New Media and Society Journal*, Vol. 10(3): 393–411.

Long, J. S. (1997). *Regression models for categorical and limited dependent variables: Advanced quantitative techniques in the social sciences number 7*. Thousand Oaks, California: Sage Publications.

Luarn, P. and Lin, H. H. (2005). Towards an understanding of the behavioral intention to use mobile banking. *Computers in Human Behavior*, Vol. 21(6): 873-891.

Lugmayr, A., Friedrichsen, M. and Muhl-Benninghaus, W. (2013). *Predicting the future of investor sentiment with social media in stock exchange investments: A basic framework for the DAX Performance Index.* Berlin Heidelberg: Springer.

Lusardi, A. and Mitchell, O. S. (2011). Financial literacy around the World: An overview. *Discussion Paper 02/2011-023, Netspar Discussion Papers*.

Lusardi, A. and Mitchell, O. S. (2014). The economic importance of financial literacy: Theory and evidence. *Journal of Economic Literature*, Vol. 52(1): 5-44.

Lwanga, M. M. and Adong, A. (2016). A pathway to financial inclusion: Mobile money and individual savings in Uganda. *Economic Policy Research Centre. Towards sustainable development research. Series No. 127*.

Maddala, G. S. (1983). *Limited dependent and qualitative variables in econometrics*. London: Cambridge University Press.

Madni, G. R. (2014). Consumer's behavior and effectiveness of social media. *Global Journal of Management and Business Research*: *E-Marketing*, Vol. 14(8): 1-7.

Maduku, D. M. and Mpinganjira (2012). An empirical investigation into customers' attitude towards usage of cell phone banking in Gauteng, South Africa. *Journal of Contemporary Management,* Vol. 9(1): 172-189.

Maertens, A. and Barrett, C. B. (2013). Measuring social networks' effects on agricultural technology adoption. *American Journal of Agricultural Economics,* Vol. 95(2): 353–359.

Mago, S. and Chitokwindo, S. (2014). The Impact of Mobile Banking on Financial Inclusion in Zimbabwe: A Case for Masvingo Province. *Mediterranean Journal of Social Sciences*, Vol 5 (9): 221-230.

Maheshwari, S. and Mittal, M. (2017). Effect of age on financial decisions. *International Journal of Advance Research and Innovative Ideas in Education*, Vol. 3(6): 1445-1454.

Mahmoud, Z. (2019). Determinants of Mobile Money Adoption. *Proceedings of the 2nd Europe – Middle East – North African Regional Conference of the International Telecommunications Society: "Leveraging Technologies for Growth",* February 18-21, 2019, Aswan, Egypt.

Maina, J. (2018). Mobile Money Policy and Regulatory Handbook. Groupe Speciale Mobile Association, Mobile Money, *GSMA Intelligence.*

Makena, K. J. and Gekara, G. (2014). Factors influencing adoption of mobile money services among institutions of higher learning in Kenya. *The Strategic Business and Change Journal of Management*, Vol. 2(20): 381-401.

Makina, D. (2012). Determinants of return migration intentions: Evidence from Zimbabwean migrants living in South Africa. *Development Southern Africa*, Vol. 29(3): 365-378.

Makina, D. (2017). The role of social media in crowdfunding. *Proceedings of the 4th European Conference on Social Media, Vilnius, Lithuania, 3 -4 July 2017.*

Marumbwa, J. and Mutsikiwa, M., (2013). An analysis of the factors influencing consumers' adoption of mobile money transfer services (MMTs) in Masvingo urban, Zimbabwe. *British Journal of Economics, Management and Trade*, Vol. 3(4): 498-512.

Mashagba, F. A. L. and Nassar, M. (2012). Modified UTAUT model to study the factors affecting the adoption of mobile banking in Jordan. *International Journal of Scientific Basic Application*, Vol. 6(1): 83-94.

Masinge, K. (2010). Factors influencing the adoption of mobile banking services at the bottom of the pyramid in South Africa, MBA dissertation, University of Pretoria, Pretoria.

Mbiti, I. M. and Weil, D. (2011). Mobile banking: the impact of M-Pesa in Kenya, *National Bureau of Economic Research*. Working Paper No.17129.

McCormick, H. and Livett, C. (2012). Analyzing the influence of the presentation of fashion garments on young consumers' online behavior. *Journal of Fashion Marketing and Management*, Vol. 16(1): 21-41.

McKay, C. and Pickens, M. 2010. Branchless Banking 2010: Who's served? At what Price? What's next? *Focus Note 66, Consultative Group to Assist the Poor*, Washington, DC.

Meyer, J. (2016). Mobile money in South Africa: what's in it for banks? [Online]. Available at:https://memeburn.com/2016/05/mobile-money-south-africa-whats-banks/ [Accessed 20/04/2018].

Mobius, M. and Rosenblat, T. (2014). Social learning in economics. *Annual Review of Economics*, Vol. 6(1): 827-847.

Montano, D., Kasprzyk, D., Glanz, K., Rimer, B. and Viswarath, K. (2008). Theory of reasoned action, theory of planned behaviour and the integrated behaviour model in *Health Behaviour and Health Education: Theory Research and Practice.* 4th Edition, San Francisco: Jassey-Bass.

Mood, C. (2010). Logistic regression: Why we cannot do what we think we can do, and what we can do about it. *European Sociological Review,* Vol. 26(1): 67-82.

Moshy. B. and Mukwaya, P. L. (2011). An assessment of adoption and use of mobile money services in East Africa-Case Studies from Uganda and Tanzania. *Proceedings of the IMTFI Annual Conference 2011.*

Muchabaiwa, H. (2013). Logistic Regression To Determine Significant Factors Associated With Share Price Change. Master of Science Statistics. The University of South Africa (UNISA), Pretoria.

Mudholkar, G. P. and Uttarwar, V. R. (2015).The impact of social networking sites on investment decisions. *Chronicle of the Neville Wadia Institute of Management Studies and Research,* Vol. 4(1): 252-256.

Mudiwa, B. (2011). A logit estimation of factors determining adoption of conservation farming by smallholder farmers in the semi-arid areas of Zimbabwe. Master of Science in Agricultural and Applied Economics Dissertation, University of Zimbabwe.

Mugambe, P. (2017). UTAUT model in explaining the adoption of mobile money usage by MSMEs' customers in Uganda. *Advances in Economics and Business*, Vol. 5(3): 129-136.

Munir, A. R. and Idrus, M. S. (2013). Acceptance of mobile banking services in Makassar: a technology acceptance model (TAM) approach. *IOSR Journal of Business and Management,* Vol. 7(6): 52-59.

Munyegera, G. and Matsumoto, T. (2014). Mobile money, remittances and rural household welfare: panel evidence from Uganda. *National Graduate Institute for Policy Studies*, Tokyo.

Murendo, C., Wollni, M., de Braw, A. and Mugabi, N. (2015a). Social network effects on mobile money adoption in Uganda. *Transformation of Global Agri-Food Systems: Trends, Driving Forces, and Implications for Developing Countries. RTG 1666 Global Food Discussion Papers No. 58*: 1-46.

Murendo, C., Wollni, M., de Braw, A. and Mugabi, N. (2015b). Social network effects on mobile money adoption in Uganda. *Proceedings of the 29th International Conference of Agricultural Economists (ICAE), agriculture in a connected world, 8-14 August, Milan, Italy.*

Nagelkerke, E. (1991). A note on a general definition of the coefficient of determination. *Biometrika*, Vol. 78(3): 691- 692.

Narteh, B., Mahmoud, M.A., and Amoh, S. (2017). Customer behavioural intentions towards mobile money services adoption in Ghana. *The Service Industries Journal*, Vol. 37(7-8): 426-447.

Ndekwa, B., Ochumbo, A. J., Ndekwa, A. G. and John, K. E. (2018). Adoption of mobile money services among students in Tanzania. *International Journal of Advanced Engineering, Management and Science*, Vol. 4(3): 149-157.

Nederpel, L. (2012). Improving the close-out supply forecast accuracy at Nike Inc. Master's Thesis, Eindhoven University of Technology, Eindhoven.

Nyagucha, M. A. (2017). Impact of social media on consumer's decision making process among the youth in Nairobi. Master in Business Administration (MBA) Dissertation. United States International University Africa, Nairobi.

O'Connell, A. A. (2006). *Logistic regression models for ordinal response variables*. Thousand Oaks: Sage Publications Inc.

Obee, J. (2012). *Social networking: The ultimate teen guide.* Lanham: Scarecrow Press Inc.

Okten, C. and Osili, U. O. (2004). Social networks and credit access in Indonesia. *World Development*, Vol. 32(7): 1225–1246.

Omotayo, F. O. and Adebayo, A. K. (2015). Factors influencing intention to adopt internet banking by postgraduate students of the University of Ibadan, Nigeria. *Journal of Internet banking and Commerce*, Vol. 20(3): 1-29.

Omwansa, T. K. (2012). Modelling adoption of mobile money by the poor in Nairobi, Kenya. Doctorate dissertation, University of Nairobi.

Onsomu, Z. N. (2015). Effect of age on investor decisions. *International Journal of Innovative Research and Development*, Vol. 4(12): 120-123.

Osborne, J. W. (2000). Advantages of hierarchical linear modeling. Practical Assessment, Research, and Evaluation, Vol. 7(1): 1-3.

Osei-Assibey, E. (2014). What drives behavioral intention of mobile money adoption? The case of ancient Susu saving operations in Ghana. *Institute for Money, Technology and Financial Inclusion Working Paper 2014-1.*

Ozdaglar, A. and Yildiz, E. (2011). Diffusion of innovations in social networks. *Proceedings of: IEEE Conference on Decision and Control 2011*.

Paluch, S. and Wünderlich, N. V. (2016). Contrasting risk perceptions of technology-based service innovations in inter-organizational settings. *Journal of Business Research*, Vol. 69(7): 2424–2431.

Papacharissi, Z. (2010). *A networked self: Identity, community, and culture on social network sites*. Eds. New York: Routledge.

Park, H. M. (2009). Regression models for binary dependent variables using Stata, SAS, R, LIMDEP, and SPSS. *Center for statistical and mathematical computing, Indiana University*. Working Paper.

Patnaik, D. and Sharma, N. S. (2013). Selection problems for application of probit, Tobit, Logit and Maximum Likelihood Estimation: A methodological issue. *International Journal of Computational Engineering Research*, Vol. 3(7): 13-29.

Pavlik, J. V. (2015). Fueling a Third Paradigm of Education: The Pedagogical Implications of Digital, Social and Mobile Media. Contemporary Educational Technology, Vol. 6(2): 113-125.

Pavlou, P. A. and Fygenson, M. (2006). Understanding and predicting electronic commerce adoption: An extension of the theory of planned behaviour. *MIS Quarterly*, Vol. 30(1): 115-143.

Pedersen, P. E. (2005). Adoption of mobile internet services: An exploratory study of mobile commerce early adopters. *Proceedings of the 10th Information Resources Management Association International Conference.*

Peifer J. L., (2011). Morality in the financial market? A look at religiously affiliated mutual funds in the USA. *Socio-Economic Review*, Vol. 9(2): 235-259.

Peng, J., Agarwal, A., Hosanagar, K. and Iyengar, R. (2014). Toward effective social contagion : A micro level analysis of the impact of dyadic network relationship. *Proceedings of the 2014 International Conference on Information Systems.*

Perlman, L. J. (2012). Legal and regulatory aspects on mobile financial services. University of South Africa, Pretoria.

Peruta, M. D. (2018). Adoption of mobile money and financial inclusion: A macroeconomic approach through cluster analysis. *Economics of Innovation and New Technology*, Vol. 27(2): 154-173.

Petrova, K. and Yu, S. (2010). SMS banking. *International Journal of E-Services and Mobile Applications*, Vol. 2(3): 9–43.

Pierre-Laurent, C. (2011). Protecting mobile money against financial crimes global policy challenges and solutions. *World Bank Publications*: Washington, DC.

Postal and Telecommunications Regulatory Authority of Zimbabwe (POTRAZ). (2018). Abridged Postal and Telecommunications Sector Performance Report Fourth Quarter 2017.

Postal and Telecommunications Regulatory Authority of Zimbabwe (POTRAZ). (2016). Abridged Postal and Telecommunications Sector Performance Report Fourth Quarter 2015.

Puschel, J., Mazzon, J. A., and Hernandez, J. M. C. (2010). Mobile banking: Proposition of an integrated adoption intention frame-work. *International Journal of Bank Marketing,* Vol. 28(5): 389–409.

Qi, J., Monod, E., Fang, B. and Deng, S. (2018). Theories of Social Media: Philosophical Foundations. *Elsevier Journal of Engineering*, Vol. 4(1): 94-102.

Qin, J. (2012). To Trade, or Not to Trade: A Model of Regret and Investment. *SSRN Working Paper.*

QWERTY (2017). Digital Statistics in South Africa 2017. *A data driven look at South Africa's relationship with digital report*.

Ramdhony, D. and Munien, S. (2013). An investigation on mobile banking adoption and usage: a case study of Mauritius. *World Journal of Social Sciences*, Vol. 3(3): 197-217.

Rao, E. J. O. and Qaim, M. (2011). Supermarkets, Farm Household Income, and Poverty: Insights from Kenya. *World Development,* Vol. 39(5): 784-796.

Refera, M. K., Dhaliwal, N. K. and Kaur, J. (2015). Financial literacy for developing countries in Africa: A review of concept, significance and research opportunities", *Journal of African Studies and Development*, Vol. 8(1): 1-12.

Rehman, F., Ilyas, M, Nawas, T. and Hyder, S. (2014). How Facebook advertising affects buying behaviour of young consumers: the moderating role of gender. *Academic Research International,* Vol. 5(4): 395-404.

Reich, B. (2015). *The Diffusion of Innovations in Social Networks*. London: University College Press.

Reserve Bank of Zimbabwe. (2016). *Retail payment systems developments in Zimbabwe.* Paper presented by Josephat Mutepfa, September 2016.

Reuters. (2016). Vodacom pulls plug on mobile money service M-Pesa in South Africa. [Online]. Available at: https://www.reuters.com/article/vodacom-groupmpesa-idUSL5N1862FF. [Accessed on September 19, 2018].

Rogers, E. (1995). *Diffusion of innovation*. 4th Edition. New York, Free Press.

Rogers, E. (2003). *Diffusion of innovation*. 5th Edition. New York, Free Press.

Rogers, E. (2005). *Diffusion of innovation.* New York: Free Press.

Rooij, M. V., Lusardi, A. and Alessie, R. (2011). Financial literacy and retirement planning in the Netherlands. *Journal of Economic Psychology*, Vol. 32(2011): 593–608.

Rotter, J. B. (1966). Generalized expectancies for internal versus external control of reinforcement. *Psychological Monographs: General and Applied*, Vol. 80(1): 1-28.

Samanez-Larkin, G. R., Kuhnen, C. M, Yoo, D. J., Knutson, B. (2010). Variability in nucleus acumen activity mediates age-related suboptimal financial risk taking. *The Journal of Neuroscience*, Vol. 30(4): 1426-1434.

Savio, C. (2012). Social media's growing influence among high net worth investors. *Cogent Research* Working Papers.

Sayid, O., Echchabi, A. and Aziz, H. A. (2012). Investigating mobile money acceptance in Somalia: An empirical study. *Pakistan Journal of Commercial and Social Sciences,* Vol. 6 (2): 269-81.

Schwartz, R. and Halegoua, G. R. (2015). The spatial self: Location-based identity performance on social media. *New Media and Society Journal,* Vol. 17(10): 1643–1660.

Schwienbacher, A. and Larralde, B. (2012). *Crowdfunding of small entrepreneurial ventures*. In D. Cumming (Eds.), *The Oxford Handbook of Entrepreneurial Finance*, New York: Oxford University Press.

Sedgwick, P. (2014). *Cross sectional studies: advantages and disadvantages.* BMJ Publishing Group Ltd.

Shaikh, A. and Karjaluoto, H. (2015). Mobile banking adoption: A literature review. *Telematics and Informatics*, Vol. 32(1): 129-142.

Shanmugham, R. and Ramya, K. (2012). Impact of social factors on individual investors' trading behaviour. *Procedia Economics and Finance*, Vol. 2(1): 237–246.

Sharma, R. and Mishra, R. (2014). Review of evolution of theories and models of technology adoption. *Indore Management Journal*, Vol. 6(2): 17-29.

Sharma, S. (1996). *Applied multivariate techniques*. Canada: John Wiley and Sons, Inc.

Shih, Y. and Fang, K. (2004). The use of a decomposed theory of planned behavior to study Internet banking in Taiwan. *Internet Research*, Vol. 14(3): 213-223.

Shin, D. H. (2010). Modeling the interaction of users and mobile payment system: conceptual framework. *International Journal of Human Computer Interaction*, Vol. 26(10): 917-940.

Shroff, R. H., Deneen, C. C and Ng, E. M. W. (2011). Analysis of the technology acceptance model in examining students' behavioural intention to use an e-portfolio system. *Australasian Journal of Educational Technology*, Vol. 27(4): 600–618.

Siganos, A., Vagenas-Nanos, E and Verwijmeren, P. (2014). Facebook's daily sentiment and international stock markets. *Journal of Economic Behavior and Organization*, Vol. 107: 730–743.

Smith, P. R. and Zook, Z. (2011). *Marketing Communications: Integrating Offline and Online with Social Media*. 5th Edition. London, UK: Kogan Page Ltd.

Solis, B. (2011). *Engage! The complete guide for brands and businesses to build, cultivate, and measure success in the new web*. Revised edition. Hoboken, NJ: John Wiley and Sons Ltd.

Sommer, L. (2011). The theory of planned behaviour and the impact of past behaviour. *International Business and Economics Journal*, Vol. 10(1): 91-110.

Statistics South Africa (Stats SA). (2015). Mid-year population estimates. P0302. 23 July 2015. Pretoria: Statistics South Africa.

Strauss, J. and Frost, R. (2011) E-marketing. 6th Edition. Upper Saddle River, NJ: Pearson Education.

Subbarao, D. (2009). Financial inclusion: challenges and opportunities. Remarks by the governor of the Reserve Bank of India at the Bankers' Club, Kolkata. [Online]. Available at: http://www.bis.org/review/r091215b.pdf.

Suki, N. M. (2010). An empirical study of factors affecting the internet banking adoption among Malaysian customers. *Journal of Internet Banking and Commerce,* Vol. 15(2): 1-11.

Suri, T., Jack, W. and Stocker, T. M. (2012). Documenting the birth of a financial economy. *Proceedings of the National Academy of Sciences USA Conference* 109: 10257- 10262.

Taylor, S. and Todd, P. A. (1995). Understanding information technology usage: A test of competing models*. Information Systems Research*, Vol. 6(4): 144–176.

Thomas, M. (2013). Diffusion of innovation in systematic review methodology: Why is study selection not yet assisted by automation? *OA Evidence-Based Medicine*, Vol. 1(2): 1-10.

Tobbin, P. E. (2010). Modeling adoption of mobile money transfer: A consumer behaviour analysis. *Proceedings of the 2nd International Conference on Mobile Communication Technology for Development, Kampala, Uganda.*

Tobbin, P. E. (2013). Towards a model of adoption in mobile banking by the unbanked: A qualitative study. *Info*, Vol. 14(5): 74–88.

Tobbin, P. E. and Kuwornu J. K. M. (2011). Adoption of mobile money transfer technology: Structural equation modeling approach. *European Journal of Business and Management,* Vol. 3(7): 59-77.

Train K. (2010). *Discrete Choice Methods with Simulation*. 2nd Edition. Cambridge: Cambridge University Press

Van Hove, L. and Dubus, A. (2019). M-PESA and Financial Inclusion in Kenya: Of Paying Comes Saving? *Sustainability*, Vol. 11(568): 1-26.

Venkatesh, V. and Davis, F. D. (2000). A theoretical extension of technology acceptance model: Four longitudinal field studies. *Management Science*, Vol. 46(2): 186-204.

Venkatesh, V., Morris, M., Davis, G. and Davis, F. (2003). User acceptance of information technology: Toward a unified view*. MIS Quarterly*, Vol. 27(3): 425–478.

Verbeek, M. (2004). *A guide to modern econometrics*. 2nd Edition. West Sussex: John Wiley and Sons Ltd.

Wachira, M. and Kihiu, E. (2012). Impact of financial literacy on access to financial service in Kenya. *International Journal of Business and Social Science*, Vol. 3(13): 42-50.

Walther, O. J. (2015). Social network analysis and informal trade. *Department of Border Region Studies Working Paper Series. Working Paper No. 01/15*. University of Southern Denmark.

Wang, L., Lu, W. and Malhotra, N. K. (2011). Demographics, attitude, personality and credit card features correlate with credit card debt: A view from China. *Journal of Economic Psychology*, Vol. 32(1): 179-193.

Wentzel, J. P., Diatha, K. S. and Yadavalli, V. S. S. (2013). An application of the extended technology acceptance model in understanding technology-enabled financial service adoption in South Africa. *Development Southern Africa*, Vol. 30: 659-673.

West, J. (2012). Financial advisor participation rates and low net worth investors. *Journal of Financial Services Marketing*, Vol. 17(1): 50-66.

Wilson, J. R. and Lorenz, K. A. (2015). *Modeling binary correlated responses using SAS, SPSS and R. ICSA Book Series in Statistics 9, Switzerland*: Springer International Publishing.

Wittink, L.T. (2011). Choice modelling. An overview of theory and development in individual choice behaviour modelling. *BMI Working Paper*.

World Bank (2015). Annual Report 2015. World Bank Group.

World Bank. (2012). *Agricultural Innovation Systems: An Investment Sourcebook*. The World Bank, Washington DC.

World Bank. (2013.) Estimating trade flows, describing trade relationships, and identifying barriers to cross-border trade between Cameroon and Nigeria. *The World Bank, Report 78283*.

World Bank. (2014). The Opportunities of Digitizing Payments? Washington, DC.

World Wide Worx. (2017). South Africa social media landscape. [Online]. Available at https:// www.worldwideworx.com/content/uploads/Social-Media-2017-Executive-Summary.pdf [Accessed 18 September 2018]

Wu, M., Chou, H., Weng, Y. and Huang, Y. (2011). TAM2-based study of website user behavior using web 2.0 websites as an example. *Wseas Transactions on Business and Economics*, Vol. 8(4): 133–151.

www.huffpost.com/entry/how-social-media-is-shaping-financial-services. [Accessed 24 September 2018].

www.statista.com [Accessed 25/11/2017].

Wydick, B., Karp-Hayes, H. and Hilliker-Kempf, S. (2011). Social networks, neighborhood effects, and credit Access: Evidence from rural Guatemala. *World Development*, Vol. 39(6): 974–982.

Xiao, J. J. (2008). Applying behavior theories to financial behavior. In J. J. Xiao (Ed.), *Handbook of Consumer Finance Research*. New York: Springer.

Xu, L. and Zia, B. (2012). Financial Literacy around the World: An overview of the evidence with practical suggestions for the way forward. *The World Bank Development Research Group, Finance and Private Sector Development Team. Policy Research Working Paper 6107.*

Yau Fu, C., Hung, J.-H., Liu, S.-H., Chien, Y.-L., 2005. A new algorithm for solving binary discrimination in conditional logistic regression, with two choices of strata. *Computational Statistics and Data Analysis,* Vol. 49 (1): 85–97.

Young, H. P. (2009). Innovation diffusion in heterogeneous populations: contagion, social influence, and social learning. *American Economic Review*, Vol. 99(5): 1899-1924.

Yu, C. H. (2012). Factors affecting individuals to adopt mobile banking: Empirical evidence from the UTAUT model. *Journal of Electronic Commerce Research,* Vol. 13(2): 104-121.

Yuan, S., Liu, Y., Yao, R. and Liu, J. (2016). An investigation of users' continuance intention towards mobile banking in China. *Info Dev*, Vol. 32(1): 20-34.

Yunus, M. (2014). Diffusion of innovation, consumer attitudes and intentions to use mobile banking. *Information and Knowledge Management*, Vol. 4(10): 12-18.

Yusuf, M. and Derus, A. M. (2013). Measurement model of corporate zakat collection in Malaysia: A test of diffusion of innovation theory. *Humanomics*, Vol. 29(1): 61-74.

Zakaria, R. H., Ismawati, N., Jaafar, M. and Marican, S. (2012). Financial behavior and financial position: A structural equation modelling approach. *Middle-East Journal of Scientific Research*, Vol. 12(10): 1396-1402.

Zarella, D. (2010). *The Social Media Marketing Book*. O'Reilly Media, Tokyo.

Zhang, Q. and Posso, A. (2017). Thinking inside the box: A closer look at financial inclusion and household income. *Journal of Development Studies,* Vol. 55(77): 1616-1631.

Zhang, Y., Lin, N. and Li, T. (2012). Markets or networks: Households' choice of financial intermediary in Western China. *Social Networks*, Vol. 34(4): 670–681.

Zhou, T., Lu, Y. and Wang, B. (2010). Integrating TTF and UTAUT to explain mobile banking user adoption. *Computers in Human Behavior*, Vol. 26(4): 760–767.

Zimmerman, J., Bohling, K. and Rotman-Parker, S. (2014). Electronic G2P payments: Evidence from four lower-income countries. *Consultative Group to Assist the Poor*, Focus Note 93/2014.

Zorlu, O. (2011). Sosyal Medyanın Cazibesi, Zorlu Dergisi, Sayı 33(6):11-23.

APPENDICES

Appendix 1: Ethical clearance certificate

UNISA university of south africa

UNISA DEPARTMENT OF FINANCE, RISK MANAGEMENT AND BANKING ETHICS REVIEW COMMITTEE

Date: 11 SEPTEMBER 2018

ERC Ref #2018/CEMS/FRMB/016
Name : Mrs S Munongo
Student #: 57638756

Dear Mrs Munongo

Decision: Ethics Approval from 01 October 2018 to 31 September 2023

Researcher(s): Name Mrs S Munongo

E-mail address **57638756@mylife.unisa.ac.za**, telephone +263773898507

Supervisor (s): Name Prof K Tsaurai
E-mail address tsaurk@unisa.ac.za, telephone 012 429 2140

Working title of research:

The relationship between social media and mobile money adoption: Comparative evidence from South Africa and Zimbabwe

Qualification: PHD FINANCE

Thank you for the application for research ethics clearance by the Unisa DFRB Ethics Review Committee for the above mentioned research. Ethics approval is granted for the period **01 October 2018 to 31 September 2023**

The Negligible ***risk application*** *was* ***reviewed*** *by the DFRB Ethics Review Committee on 11 September 2018 in compliance with the Unisa Policy on Research Ethics and the Standard Operating Procedure on Research Ethics Risk Assessment*

University of South Africa
Preller Street, Muckleneuk Ridge, City of Tshwane
PO Box 392 UNISA 0003 South Africa
Telephone: +27 12 429 3111 Facsimile: +27 12 429 4150
www.unisa.ac.za

Open Rubric

Appendix 2: FinScope South Africa 2015 Questionnaire

-

Project FinScope SA 2015
Questionnaire
METRO
Job No: 233103958

Cape Town (Head Office) TNS House 6 Thicket Road Newlands 7700 Ph: (021) 657-9500	Johannesburg TNS House, Stonemill Office Park Cnr Republic Road & 300 Acacia Road Darrenwood 2194 Ph: (011) 778-7500	Durban 4 Sunbury Crescent Sunbury Park La Lucia Ridge 4051 Ph: (031) 571 4900

DP:	Query (1)	Omission (3)	Redo (5)	Late (6)	Excluded (8)
Yes	-1	-1	-1	-1	-1
Item numbers	(2)	(4)		Date (7)	

	Signature	Code (9)
Debriefed by		
Edited by:		
Coded by:		
Coding checked by:		
Consistency checked by:		
Editing checked by:		

QC:	B/Checked by (10)	Type of backcheck (11,12)		Date	Code (13,14)
QC	-1	Phone: -1	FtF: -2		
F/Manager	-2	Phone: -1	FtF: -2		
F/Worker	-3	Phone: -1	FtF: -2		

Respondent number: (15)

QC Dept outcome (16):	-1	-2	-3	-4	-5
	Extr Satisfactory			Extr Dissatisfactory	

Comments:

Date d d / m m / y y y y (record day / month / year) **(30,31,32)**

INTERVIEW DETAIL

Questionnaire Number		**(17)**
EA Code		**(18)**
Province		**(19)**
Sample Interval		**(20)**
Field Manager		**(247)**
Area		**(248)**

(22)
VISITING POINT NUMBER

PARTICULARS OF THE VISITING POINT

(40)

OFFICE USE ONLY	
ORIGINAL VISITING POINT	-1
SUBSTITUTE VISITING POINT	-2

<u>Final respondent:</u>
Name of respondent: ....
Address of respondent:
Complex / Flat Nr:..................(41) Complex / Flat Name: ....(42)

Street Nr:..................(43) Street Name: ....(44)

Suburb:..................(45)Town: ....(46)

Tel. No: (H) (47)..................(48) (W) (49)..(50)

Cell No: (51)..(52)

Interviewer: ....(26)

Field Manager: ....(27)

Start Time [ ][ ] H [ ][ ] (record using 24 hr clock, for example 1500 and not 3pm) (28,29)

Appendix 3: FinScope Consumer Survey Zimbabwe 2014 Questionnaire

Project FinScope Consumer Survey Zimbabwe 2014 Questionnaire. Job number RC010052014 FINAL 31-07-2014

RESEARCH CONTINENTAL-FONKOM

Date of Study ______ *Household No.* ______

Length of Questionnaire/Interview ______

Locality Name ______

1.A **RESPONDENT INFORMATION**

Respondent Name : ______

Address: Number/Street : ______

Suburb : ______

Town : ______

Provincial code :	1	2	3	4	5	6	7	8	9	10
Urban/rural :	Urban	1			Rural	2				

EA Area Code ______

Cell phone number : ______

Landline : ______

Interviewed by ______

Supervised by ______

Back checked. (Name and Date) ______

B.RESULT OF SELECTED HOUSEHOLD INTERVIEW:

SUCCESSFUL	1
NO ONE AT HOME/CLOSED	2
ABANDONED	3
REFUSED	4
RESPONDENT AWAY	5
OTHER (SPECIFY)	6
SUBSTITUTE HOUSEHOLD	7

TIME START

TIME END

DP NO.		BATCH NO.		LISTING NO.	