2020

The Role of alternative data in accurately determining credit score for mobile lending on digital wallets in Kenya

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34201/2017

Master of Public Policy and Management

June 2020

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A Research Dissertation Submitted to Strathmore Business School as a Requirement in the Partial Fulfillment for the Master of Public Policy and Management of Strathmore University

Strathmore Business School

Strathmore University

Nairobi, Kenya.

June 2020

DECLARATION

I declare that this project has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the project contains no material previously published or written by another person except where due reference is made in the proposal itself.

Signed: ________________________

Date: ___30th June 2020_______________

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The research dissertation has been presented for examination with my approval as the appointed university supervisor.

Signed: ________________________

Date: __________________

Dr. Vitalis Ozianyi

ABSTRACT

The increased call for global financial inclusion especially for the low income earners, has resulted to increased use of mobile lending on digital wallets. The purpose of this study was to describe the role of alternative data in accurately determining credit score for mobile lending on digital wallets in Kenya. Alternative data as independent variables included social network data, mobile phone data and transaction data. The study employed a descriptive survey design to meet the research objectives. Primary quantitative data were collected using questionnaire tool. The survey was conducted to a 350 sampled respondents of mobile lending application users; where 230 were individuals while 120 were informal micro enterprises using mobile money applications. Scientific and non-probability sampling methods were used. Descriptive analysis and multivariate analysis through ordinary linear regression was used to develop the model of the study. Also, principal component analysis was conducted to describe the dimensionality of the dataset. Reliability and validity of the research instruments was determined to ensure that the information gathered addresses the research problem. Diagnostics tests such as normality test and multicollinearity tests were performed. The study findings on regression analysis to determine the relationship between social network data, mobile phone data and transaction data and credit score for mobile lending on digital wallets established that of the three independent variables of the study; there was significant positive relationship between transaction data and credit score for mobile lending on digital wallets in Kenya. That is, consumers' increased transaction records improves their credit score. The results also revealed that there was insignificant positive relationship between social network data and credit score for mobile lending on digital wallets. Lastly, findings revealed that there was a significant inverse relationship between mobile phone data and credit score for mobile lending on digital wallets. On policy implications, the study recommends that both the government and mobile lending providers should design clearer policy frameworks that streamline the use of alternative data such as transaction records of consumers. Also, there is need for mobile wallet providers to adhere to regulations of privacy and educating their borrowers on the importance of having accurate information on their social media accounts that reflects their personalities. This also formed the knowledge contribution of the study. Since this study was carried out on individuals and informal micro enterprises, this study recommends that a similar study should be undertaken in the future but with Fintech or mobile lending providers as the target respondents.

Key words: Alternative data, credit score, digital wallets, mobile lending applications

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
CBK	Central Bank of Kenya
CGAP	Consultative Group to Assist the Poor
DOI	Diffusion of Innovation
Fintech	Financial technology
GDP	Gross Domestic Product
GSMA	Groupe Spéciale Mobile Association
MNO	Mobile Network Operators
NPL	Non-performing loans
PCA	Principal Component Analysis
P2P	Peer-to-peer
SME	Small and Medium-sized Enterprises
SMS	Short Message Service
SPSS	Statistical Packages for Social Sciences
US$ (USD)	United States Dollar

CHAPTER ONE

INTRODUCTION

1.1 Introduction

In order to describe the purpose of the study objectively, this chapter discusses the background of the study, problem definition, research objectives, research questions, scope of the study and significance of the study as provided.

1.2 Background of the Study

Mobile credit access in Kenya has gained prominence in the past one decade, hence transforming access to credit. Jenkins (2008) defined Mobile Money as cash accessed and used through the mobile phone technology. According to Blechman (2016), the latest expansion of financial service provision through mobile in the least developed countries has resulted to increased access to financial services among the low income earners as well as the high percentage of the unbanked population. Nzayisenga (2017) indicates that the concept of digital money is an evolving form of financial service that gives customers or borrowers opportunity to have access to quick money/loan through their mobile devices. In Kenya, mobile loan services attained faster growth due to stringent requirements to access loans from mainstream financial institutions making low income earners to miss financial services (Nordigen, 2017).

Blechman (2016) refers to mobile credit as the ability of consumers to quickly apply for and get loans through their mobile devices by avoiding the time, stringent measures and paperwork of mainstream financial institutions loan application. This model of financial credit access involves assessment of mobile credit usage enabling the underserved to acquire credit through their phones (GSMA, 2016). According to Hamp, Agwe and Rispoli (2016), mobile credit products have embraced three dimensions through digitization to effectively establish credit capacity and they involve applicant's repayment capacity analysis, loan disbursement and history of repayment. Mobile credit providers are unique in that they are instant, automated and remote.

Globally, consumers have remained invisible when it comes to credit accessibility. For instance, findings from the Consumer Financial Protection Bureau indicate that 45 million Americans cannot be scored by the traditional credit rating agencies because they have no credit history, limited or outdated history. Moreover, despite millennials having mobile phones, only one third of Americans aged between 18 and 29 have a credit card (Lee, 2020). As a result, it is argued that use of alternative data may prove significant to improving the status quo by enhancing the accuracy of existing scores (attaining better risks separation), and rendering visible of many of today's credit invisibles in the U.S. Due to market developments, consumer lending has moved towards the practice of making lending decisions guided by statistical models, and lenders evaluate their borrowers through underwriting process that relies heavily on their credit score obtained from their credit files (Caroll & Rehmani, 2016).

Accelerating digitization of transactions is creating an increasing types and volume of consumer data, providing additional pool of information that lenders can possibly utilize to determine a borrower's credit worthiness (Holmes, 2020). In emerging markets such as Sub-Saharan Africa, carrying out due diligence desirable to assess an applicant's credit risk is a challenge for various reasons: geographic inaccessibility and little to no information to the individual's credit history. However, modern data sources such as alternative data is proving to be essential. In Ghana for instance, digital lenders apply mobile usage to assess not only an individual's credit risk but also the probability that the person will use a particular financial services or product. The company uses additional financial information such as water, utilities and education payment history to assess credit risks of their borrowers (Cov Africa, 2015).

Further, the rise of mobile financial services has been promoted by advent of mobile money that enables users to access cash through their mobile devices (Jagtiani & Lemieux, 2018). In Kenya, mobile credit has achieved tremendous success with the market being considered a mature market for mobile financial services (Blechman, 2016). However, despite all these milestones, policy frameworks remains a challenge for mobile credit services. Moreover, there is still little information on how mobile credit providers establish their credit score model of their consumers. Previous studies have attempted to highlight the effectiveness of social network data, phone data and transaction data (Williams, 2016; Huang, 2019; Jayakumar, 2019) in developing individual credit score model. However, the relationship between these perceived data have not been explored in in-depth, especially in the context of Kenyan growing mobile credit services.

In response to this challenge, and to enhance policy frameworks that can result to implementation of effective credit score model among mobile money wallet providers, this study sought to describe the role of alternative data using the aforementioned data, that is, social network data, mobile phone data and transaction data in accurately determining the credit score for mobile lending on digital wallets. The study focused on users of the registered mobile lending providers in Kenya mostly, M-Pesa through Lipa na M-Pesa overdraft services, Tala, Branch, Mshwari and KCB-M-Pesa which are product of partnership between Safaricom, NCBA and KCB banks respectively. Users comprised of both individual and informal micro enterprises.

1.2.1 Mobile Money Lending and Alternative Data in Kenya

Mobile money service is expressed as a wide concept that has emerged out of electronic payment and banking industry. Jenkins (2008) defined Mobile Money as cash accessed and used through the mobile phone technology. The increased penetration of mobile phone technology in emerging markets has enabled mobile money to gain reputation in the Kenyan economy (Wamaitha, 2016). According to Ndegwa (2014), the Kenyan context of using mobile phone technology to access money transactions has been very successful in ensuring cash availability to the rural populations. Thus, mobile money is not just a fad, but a great phenomenon in the Kenyan financial sector.

The emergence of technology has created financial awareness and availability to poorer and low income earners with no access to banking services especially in developing nations (Mohamed, 2013). The Central Bank of Kenya (CBK) indicates that transactions made in 2018 amounted to US dollar 38.5 billion through the real-time mobile-based payments. There has been a steady increase in mobile money transactions. A total of 4.35 trillion was moved through mobile phones in 2019 compared to 3.98 trillion in 2018, representing a total transactions increase of 361.39 billion (Central Bank of Kenya, 2019). The steady increase has majorly been attributed to the rise in uptake of mobile loans offered by various entities and mobile wallets, and is referred to as mobile lending.

Mobile lending is a service provided by mobile phone operators in conjunction with financial institutions allowing customers to conveniently access cash and credit using their phones (Nzayisenga, 2017). The structure allows unbanked and rural area customers with no bank accounts to access financial services. Many low income earners and informal Small and Medium sized enterprise (SME) operators have been relying on mobile lending to access credit especially after the capping of commercial lending rates in 2016 (Murunga, 2017). The capping of interest rates resulted in many low income earners being left out in credit access due to lack of collateral or security for getting loans. However, the proliferation of mobile lending is improving credit access to many without the need for security and only utilizes alternative data and credit scores to determine credit accessibility (Blechman, 2016).

According to Aydin and Burnaz (2016), alternative data refers to the non-financial client information that is utilized in the estimation of lending capacity and risk of an individual. The data incorporates utility bills like gas, electricity; telecommunication bills and rental payments. It is estimated that 45-50 million clients in emerging economies do not have sufficient data to support their credit score or information for any consumer lending decision making (Carroll & Rehmani, 2017). Alternative data is perceived to have significant potential to improve the status quo by enhancing the accuracy of lending scores through achieving better risk separation and rendering many clients able to access credit facilities.

Types of alternative data may include social network data, mobile phone data and transaction data. Previous study findings indicated that these types of data are essential in developing effective credit scoring model for consumers using statistical methods (Westerlund, 2019; Caroll & Rehmani, 2016). Lenders uses applicants' information such as LinkedIn, Facebook, Twitter and Instagram accounts; data subscription, application usage, GSM and SMS records; as well as utilities bill payments like electricity, fee payments and rents (Majumder, 2019; Eilin, Blumenstock, & Robinson, 2017; Nordigen, 2017). Fintech firms uses these information to determine behavioral analysis of their consumers towards loan repayment (Majumder, 2019). According to Argawal et al., (2018), alternative data is significant in predicting an individual's credit risk. However, the knowledge and understanding of borrowers on how Fintech firms uses these types of data in creating credit score for consumers remain low. The study therefore included the types of alternative data as the independent variables of the study.

1.2.2 Mobile Wallet Providers

Mobile wallet providers are companies offering mobile money services through applications installed in mobile devices (Singh, Srivastava, & Sinha, 2017). The financial transactions are carried out in cooperation with banking institutions where clients' information is shared and transactions carried out effectively. A mobile wallet refers to a method of carrying ones credit card or debit card data in a digital form within the mobile device. This enables users to use their Smartphones or Smart watches for transactions rather than carrying physical plastic cards to make purchases (Manikandan & Jayakodi, 2017). The increased use of mobile phones and

Smartphone technology has seen an upsurge use of mobile wallet as providers come up to ease credit access.

Mobile credits are unsecured and relies on credit evaluation to establish credit worthiness based on relevant algorithm analysis instead of loan repayment history making this a high risk loan (CGAP, 2014). Thus, loans given are typically small, shorter and significantly costly than traditional consumer loan products with interests that range from 2% to 10% on a monthly basis (Hwang & Tellez, 2016). The interests are mostly assessed as a flat fee, irrespective of even repaying the loan before the time lapses. For example, a one month loan repaid after three days would attract full monthly interest charge thus, making the annualized rate enormous. Nevertheless, in spite of the high costs, mobile credit have become an attractive form of credit access to low income earners as they are faced by constraints and high operating costs from mainstream financial banks (GSM Association, 2014).

Singh, Srivastava and Sinha (2017) looked into the consumer preference and satisfaction of mobile wallets among North Indian users and found that awareness has impacted on the usage. The study established that mobile wallets provide ease and convenience of credit access via the mobile technology. Verkade (2018) on the developing consumer adoption of mobile wallet in Canada found out that perceived security is one of the most concerned factors affecting adoption among consumers. However, the study identified improved awareness could enlighten users on various values and features that would help in effective financial management. Thus, it is apparent that mobile wallet is a global phenomenon that is proliferating at faster rate.

As a result, mobile wallet providers are relying on alternative data to develop credit score for their clients. Credit score has evolved from use of non-traditional means of scoring clients to use of alternative data. However, despite its increase in use especially in mobile lending digital services, there is little knowledge of use of alternative data among mobile lending consumers.

1.2.3 General Mobile Lending Applications

Over the years, money lending function has been primarily a preserve for traditional banks or commercial banks across the world. Accessibility of credit from these institutions remained a nightmare for the majority of the low income earners globally. This has led to the increased call for financial inclusion by various world bodies (Verkade, 2018). Interestingly, the growing technological use and level of innovation have seen rise to new credit facilities in the form of mobile money lending applications. The objective of these mobile money applications is to reach out to the excluded credit consumers who are low income earners and do not have valid credentials to access credit from traditional banks (Aydin & Burnaz, 2016).

Therefore, mobile lending providers have developed mobile applications that provide users with ease of access to credit and other financial services through mobile platform with the aid of technology. The effectiveness of mobile money lending applications is that they can be easily downloaded from the internet among others, Google Play Store (Hwang & Tellez, 2016). The flexibility of mobile lending applications has largely resulted to increased rise in digital lending in emerging economies, Kenya being an example. Moreover, the effectiveness and efficient nature of mobile lending application is that it does not require any form of collateral, as the providers conduct minimal credit risk assessment for the their borrowers, with faster processing of loans which is accessible to the larger population of the low income earners (Hwang & Tellez, 2016).

All these features of mobile money lending through digital platform has made lending more appealing to the borrowers. A number of mobile money wallets exist in Kenya. From the CBK report (2019), there are over 20 fully registered mobile money lending providers with majority using digital platforms to reach their consumers. Major players in the mobile money lending market include M-Pesa, Mshwari, Branch, Tala and KCB-M-Pesa among others. The study target users of these mobile money providers. One of the mobile money lending applications that has been active in providing access to loans through digital platform is Tala App (application). Tala app has been in operation in Kenya since 2014 and also has presence in India, Philippines and Mexico (Agarwal, Lin, Chen, & Singh, 2018). Additionally, Tala was able to disburse close to US$1 million in loans within its first six months of operation in Kenya (Herbling, 2016). Plans are underway to expand to new markets and increase its customer base which stands at 750,000 and US$30 million in originated loans with an approximate 10% default rate (WAPI Capital, 2018).

The motive of the study to involve mobile money lending applications users was to provide knowledge and understanding of how these digital lending providers develop a credit score and provide financial credit to the people. Despite studies addressing effectiveness of mobile money lending in Kenya, little information is available to indicate the relationship between use of alternative data and credit score for mobile lending on digital wallets. In an environment where regulation and policy frameworks remain low and inactive, the study may be significant to the policymakers and to the mobile lending providers in emphasizing the need for robust framework policies in developing a good credit score model for the consumers using non-financial data such as social network account, mobile phone data and transaction data.

1.3 Problem Statement

The call for alternative data usage in determining applicant's credit score is increasing among scholars and Fintech practitioners. Globally, a high number of consumers have remained invisible due to lack of adequate data by the lending institutions. In U.S for instance, despite individuals aged between 18 and 29 years having mobile phones, approximately a third of them do not have effective credit score (Holmes, 2020; Caroll & Rehmani, 2016). However, the emergence of mobile money lending concept has changed the financial landscape in emerging economies (Murunga, 2017). Digital lending has created a platform for most informal micro businesses and individuals of lower income to have access to financial services through their mobile phones. Thus, digital wallets have improved the achievement of financial inclusion among people in the least developed nations (Al-Jabri & Sohail, 2012). Due to inability to provide collateral assets to access loans in the traditional banks, mobile money lending applications has developed mechanisms such as alternative data of an individual that they use to create credit score for everyone seeking mobile loan with them. The providers use artificial intelligence (AI) to process alternative data such as social accounts information, transaction records and mobile call records that have essential information of the borrower.

However, in as much as there has been growing use of financial innovation which has led to the rise of mobile money lending services, ineffective policy frameworks and lack of clear understanding of how digital finance providers use available alternative data has remained a challenge for many. Also to note is that many people do not understand how mobile money providers develop their credit score. A review of the literature has established various alternative data that mobile lending providers use to create credit score (Jayakumar, 2019). However, it is important to acknowledge the conclusions made by various studies that despite having these data, creating a sound and effective credit score still remains a challenge for many mobile lending institutions; this has affected their level of operations since a good number of them still have high default rates among their borrowers (Nzayisenga, 2017). In response to this challenge and to attempt and develop policy recommendations which will be important for the policymakers and practitioners, this study sought to describe the relationship between alternative data and credit score for mobile lending on digital wallets.

1.4 Research Objectives

The general objective of the study was to describe the role of alternative data in accurately determining the credit score for mobile lending on digital wallets.

1.4.1 Specific Objectives

The specific objectives of the study included;

i) To establish the relationship between social network data as an alternative data and credit score for mobile lending on digital wallets.
ii) To investigate the relationship between mobile phone data as an alternative data and credit score for mobile lending on digital wallets.
iii) To determine the relationship between transactions data as an alternative data and credit score for mobile lending on digital wallets.

1.5 Research Questions

The study was guided by the following questions;

i) What is the relationship between social network data as an alternative data and credit score for mobile lending on digital wallets?
ii) How does mobile phone data as an alternative data relates to credit score for mobile lending on digital wallets?
iii) Does transaction data as an alternative data has a relationship with credit score for mobile lending on digital wallets?

1.6 Scope of the Study

The study explored the role of alternative data in determining the credit score for mobile lending on digital wallets. The study focused on the users of mobile lending applications - both at individual and informal micro businesses level. The study mainly considered three types of alternative data to be identified such as social network data, mobile phone data and transaction data. Further, the study sought to highlight how using these alternative data affects credit scoring for mobile money lending on digital wallets. The advantage of involving individual and informal micro businesses as the target group is that it allowed the study to illustrate various information regarding alternative data that mobile lending providers considers in dispatching online loans to their customers. This may include age, purpose of borrowing and individual or group objectives. The scope of social data was Twitter account, Facebook account, Instagram account and LinkedIn account. Mobile phone data included GSM call and SMS logs and duration of subscription, application usage and data subscription; transactions data included M-Pesa records, online/offline bill payments and traditional bank account transactions. The study period was from May 2019 to April 2020.

1.7 Significance of the Study

The study is significant in the following ways;

1.7.1 Mobile Lending Institutions/Practitioners

The study may be significant to the mobile money lending services by establishing how to effectively access clients' data for sustainable credit lending. Understanding approaches of accessing and trailing clients' data from mobile wallets is essential to mobile money lenders to reduce the risk and cost of borrowing. This will be important in developing top policy policies that will streamline the operations of mobile money services. The achievement of centralized data access, as well as credit score would help to identify genuine customers and avoid defaulters. The findings of the research may help mobile credit lenders on how to effectively leverage on alternative data from mobile wallets to solve the problem of information asymmetry and enhance credit access.

1.7.2 Academia

Further, the study may form a pool of academic findings for future researchers on mobile money lending and credit access to build on and expand on the concepts. The mobile financial service phenomenon is a developing one and continuous studies are inevitable to promote efficient innovations in the future.

1.7.3 Government and Policymakers

The need for effective financial innovation regulations has continued to form part of financial market debate in Kenya. The findings of the study may prove beneficial in guiding policymakers to develop effective policy frameworks on how to regulate digital lending operations and the use of alternative data in developing consumer credit score. This will be to ensure that Fintech firms adhere to privacy issues when handling consumer information to create their credit score.

1.7.4 Credit Consumers

Majority of borrowers have continued to access digital lending in terms of limited amount they can borrow without deeper knowledge or understanding of how lenders arrive at such credit limits. The findings of this study provides consumers with an opportunity to understand the usefulness of alternative data in developing their credit score, and the need for them (consumers) to put forward credible information that improves their creditworthiness.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter presents the literature review on role of alternative data in accurately determining the credit score for mobile lending on digital wallets. Literature review looked at the existing studies that have been undertaken by various scholars so as to help in guiding the objectives and aims of the study. Thus, this chapter presents the theoretical review of the study, the empirical review, conceptual framework and research gap.

2.2 Theoretical Review

The concepts of credit access and use of alternative data by mobile lenders forms the basis of this research. There are a number of theories that have been developed, however, the theoretical approach taken by this study embraces two theories to explain the concept of adoption of technology and innovation to leverage credit access and the use of intermediaries. The innovation diffusion theory and financial intermediation theory were reviewed and discussed in respect to the context of alternative data and credit score in mobile technology

2.2.1 Diffusion of Innovation Theory

Diffusion of Innovation (DOI) theory was developed by Rogers in 1962 and explains the manner in which human beings as part of social system adopt a new idea, behavior or product (Rogers, 2003). The concept of adoption means someone doing something differently than the previous trends through innovation and this is possible through diffusion. Rogers developed the DOI theory seeking to expound that innovation is taken up in society and postulated five categories of adopters in respect to technology (Wani & Ali, 2015). In the first category are the innovators who create new ideas in technology and experiment it by themselves. (Rogers, 2003). The second group involves the early adopters who are conversant with the technology and interested in using it for professional and academic purposes to create solutions (Al-Jabri & Sohail, 2012). Generally, these are the opinion leaders who enjoy leadership roles and embrace change opportunities.

Thirdly, the early majority involve individuals who are practical in nature and adopt new ideas before the average individuals (Rogers, 2003). However, they require evidence of the innovation effectiveness and success stories to be convinced. The fourth group is the late majority involving individuals not at ease with technology and is skeptical about its use and mostly makes half of the normal group (Bohlina, Gruber, & Koutroumpis, 2010). They only try the innovation once it has been tried by the majority and ascertained successful. Thus, campaigns on the success of the technology are utilized as a strategy to appeal to this group. Finally, the laggards involve the ones who are very conservative and may never adopt technology (Al-Jabri & Sohail, 2012). Usually, they can be critical and antagonize others not to adopt the technology. This group appealed to statistics and pressure from other adopter groups.

In the mobile technology era, mobile lending is one example of innovations that have become very successful in recent years improving business operations. According to Rogers (2003), innovation involves a deliberate application of information to generate unique ideas within a given area of operation. Mobile lending is a technological innovation that has proliferated from mobile telephone aimed at improving financial services among the unbanked (Singh, Srivastava, & Sinha, 2017). Further, Wani and Ali (2015) state that mobile phones emergence in the global markets has transformed the world beyond the expectations of many. Through the small innovation, millions of lives in world have been transformed tremendously. New technology is a key aspect to innovation and is influenced by its usefulness, compatibility, complexity and capacity to be observed (Mwangi & Bwisa, 2013).

In essence, the concept of using alternative data in mobile lending is an innovative way of accessing client information to establish credit score and promote operations in mobile lending (Manikandan & Jayakodi, 2017). Mobile wallet providers have developed effective ways through statistical models that they utilize to gather enough information concerning their applicants. Such techniques include incorporating their transaction data such as utilities payments and mobile phone data through various application downloads or usage. When consumers download such applications provided by mobile wallet providers, their transaction data as well as utility payments are automatically reflected by the aid of AI, making it easy for them (providers) to develop their applicants' credit score.

2.2.2 Financial Intermediation Theory

Financial intermediation theory was proposed by Akerlof in 1970 with contributions later by Spence in 1973 then Rothschild and Stigliz in 1976. The theory holds the phenomenon that financial intermediaries exist as they are able to bring down the cost of transaction brought about by information asymmetry between borrowers and lenders (Allen & Santomero, 1997).

The essence of intermediaries is to ensure effective functioning of the financial markets. The use of mobile wallets for alternative data acts as an intermediary in mobile lending by giving crucial information on potential clients' lending capacity (Nzayisenga, 2017).

The theory of financial intermediation is based on two main foundations, with the first explaining the importance of financial intermediaries in provision of liquidity to financial institutions (Freixas & Rochet, 2008). While the second one involves the ability of financial intermediaries to transform the risk characteristics of assets in credit lending (Howells & Bain, 2007). The two foundations possess the capacity to reduce cost of operations between the borrowers and lenders and hence, resulting in more efficient allocation of resources. Financial intermediaries have the ability to transform the risk characteristics of assets and enable them to circumvent the market failure and thus, addressing the information asymmetry problem.

The aspect of information asymmetry involves borrowers having more information about their investment projects compared to lenders and can occur either ex ante or post ante. Ex ante information asymmetry involves when lenders are not in a position to distinguish between borrowers having different credit risks before advancing loans to them (Allen & Santomero, 1997). Such a situation results in adverse selection problems of who to lend credit. Post ante information asymmetry occurs when only borrowers, but not lenders, are able to observe actual returns after project completion. This in turn brings up a moral hazard; a situation whereby the borrower engages in activities that are most likely to result in loan repayment default (Nzayisenga, 2017).

This theory is very important in this study as it highlights challenges of credit lending facilities in assessing the credit worthiness of a borrower on mobile platform resulting in adverse selection. Mobile wallets in this study formed a part of the intermediaries to be evaluated on their capacity to use alternative data for credit risk and capacity analysis. Although borrowers may have no collateral or assets as security, having diverse information that positively improve on their financial capacity and ability to pay may promote their credit access process (Manikandan & Jayakodi, 2017). Thus, the use of alternative data as a way of establishing capacity and credit score of borrowers in mobile lending is expected to leverage on information asymmetry as described by the financial intermediation theory. This theory therefore can be connected to social network data where lenders due to their inability to have adequate information about borrowers, utilizes these information from the applicants' social accounts to model their behavioral analysis towards loan repayment.

2.3 Empirical Review of the Literature

This section discusses the previous studies on the current study based on each independent variables; social network data, mobile phone data and transaction data. Under each study variable, the study starts by highlighting the concept or definition of the data then discusses the previous studies based on the author(s), methodology where possible and findings.

2.3.1 Social Network Data

While social media has been viewed as a social tool, to the Fintech experts it remains an important tool that can provide essential data for determining the credit risk of an individual. Social media may have a very important effect on an individual's credit and his or her ability to get loans. It can be argued that financial firms look at social media data or sites when making lending decisions. The goal is not only to identify the identity of the borrower but to also determine the credit worthiness of an individual (Carroll & Rehmani, 2017). Thus, lenders are interested in the borrower employer's information and comparing what is stated on loan application to what is available on the social media accounts such as Facebook or LinkedIn. However, the challenge has remained in terms of quantifying the information available since most of the applicants do not have knowledge on the importance of such data from their social media accounts (CGAP, 2014).

Zhang, Jia, Diao, Hai and Li (2016) researched on credit scoring by fusing social media information in online peer-to-peer lending in China to determine loan default. The study adopted decision tree as one of the most widely utilized classification and prediction method of machine learning. Also, the methodology is preferable due to its ability to use both numerical data and non-numerical data. Data used were obtained from www.ppdai.com between January 2014 and September 2014. Also, social network information of the applicants were grabbed using their user identification. The results indicate that the model has good classification accuracy. That is, loan information, social media information and credit information are most important factors for predicting the default of the consumers.

Wei, Yildirim, Van den Bulte and Dellarocas (2015) also examined how social network data may improve credit score of individuals especially in the low income bracket. In an attempt to determine how the accuracy of an individual's social network data may improve their credit scores, the study developed various models to compare the accuracy of individual scores obtained with and without social network data. Their study findings established that people are motivated to improve their scores by forming fewer ties but focusing on more similar partners. The scores therefore can become more accurate as a results of improved social networks, but the accuracy improves with higher network fragmentation. However, the report did not elaborate ways in which social network can be improved to attain high credit scoring and the extent of such high credit scoring attained.

Niu, Ren and Li (2019) tested the reliability of social network information in predicting loan default in peer-to-peer lending. The study retrieved social network information of borrowers from their mobile phones and then used logistic regression to establish the relationship between social network information and loan default. Three machine learning algorithms – AdaBoost, LightGMB and random forest were created to show the predictive performance of social network data. Results from the logistic regression of the study demonstrated that there is a statistically significant relationship between social network data and loan default. Further, findings illustrate that social network information can improve loan default prediction performance significantly. As a result, these information is significant in credit scoring. However, there is limited research in this area in Kenya.

Williams (2016) examined how credit scoring firms always watch every move of individuals seeking credit with them. The study established that in China and US, credit firms have been experimenting with social medial data or profiles. Who one is connected with on their social medial account can help in boosting his or her credit score. Most lending firms that do peer-to-peer lending affirmed that they are more likely to give loan to people who are friends to the people they have lent money to before and paid on time as to some extent, it reveals trustworthiness (Williams, 2016). Williams argues that social network data also has challenges since information gathered from a person's profile might be small and false. Thus, this study sought to illustrate how lending firms utilize these information available on social media accounts to improve credit score.

Tan and Phan (2018) investigated social media-driven credit scoring based on predicting value of social structures. The study argue that while emerging economies have seen expansion in internet population, these economies do not have credible credit scoring systems or credit bureaus to predict creditworthiness of individuals. Leveraging on the widespread adoption of social media and social network sites, the study obtained anonymized backend data from microfinance institutions which offers microloans in Southeast Asia country. Bayesian method of social network-based credit scoring and helps in addressing network sparsity and data scarcity with egocentric networks were used. Empirical analysis reveals that fusing social network data can improve creditworthiness prediction in microfinance institutions. That, social network-based can be an effective approach for credit scoring in developing countries that face financial exclusion challenge.

Majumder (2019) found out that the traditional credit scoring by big banks and financial institutions is slowly shifting after it emerged that Fintech firms are developing effective ways of accessing the unbanked population. The study argue that in the previous model of credit scoring, majority of the population often felt left out. As a result, alternative credit scoring models such as social media data have emerged and are considered as more inclusive than traditional credit scoring methods (Majumder, 2019). The findings further suggest that most start-up firms especially Fintech focus more on conducting social medial behavioural analysis using the available network data so as to estimate the creditworthiness of a person. Thus, the information obtained from various social media accounts such as Facebook, Twitter and LinkedIn assist lenders in developing more accurate credit profile of borrowers and their personality towards loan repayment.

According to a study by Lohr (2015), a growing number of start-ups which targets low income earners claim that using social network data as a credit scoring provides opportunities for many individuals in the low income categories who may have found it difficult to access credit from big banks to access loan from their platforms. Chui (2013) also found out that Fintech firms assign credit scores based on the data obtained from an individual's social networking data like education and employment history, number of followers they have, types of friends and data about these friends. Jenkins (2014) found out that due to the growth of Fintech services, an increasing number of lending firms are relying more on network based or social media data to determine borrower creditworthiness.

2.3.2 Mobile Phone Data

Due to the nature of traditional banking that do not enable credit facilities to the majority of people who are considered risky and unbanked, Fintech businesses have aimed at feeding this market with efficient financial services that meets their needs and demands (Huang, 2019). It was established that close to 39% of individuals who took credit facilities used informal sources such as mobile money loans while only 3% borrowed from banks in Philippines. Therefore, Fintech firms must find effective ways of developing mechanisms to credit scoring by looking beyond traditional approach (credit bureau database) and using other sources such as mobile phones. It showed that mobile phone data are available, accessible and replete with important information that Fintech firms use for credit-scoring. Mobile data is useful in indicating a borrower's lifestyle and economic activity (Huang, 2019). In conclusion, it was revealed that how an individual organizes his or her contacts (such as first name and last name) and how they structure their short messages (grammar and punctuation) can be helpful as data points in the credit scoring model.

According to Pritchard (2019), utility payments such as electricity, rent, shopping and insurance may not have much relationship with traditional credit score by banks and other financial institutions. However, the data gathered from such activities is quite useful as an alternative credit scoring data by Fintech and other financial start-up firms, especially from phone data. Families and individuals do make multiple payments to various organizations every month. And these are data that should not go into a waste. Pritchard indicates that Fintech firms uses these data to establish the credit risk of an individual so as to grant loans. People who don't pay their utility bills will most probably have a low credit rating hence cannot have access to loans given by Fintech firms. Agarwal, Lin, Chen and Singh (2018) in their study on predicting financial trouble using call data using 180,000 individuals as the target population on a span of 2 years; together with 82.2 million monthly bills and 350 million call logs established that phone based data is significant in predicting an individual's credit risk.

Mobile phones have spread drastically to over 4.5 billion in emerging economies. Apart from improving communication, mobile phones also provide new forms of credit. To establish whether this statement is effective, Bjorkegren and Grissen (2015) demonstrated a method to predict default among borrowers without formal financial histories, using behavioural patterns revealed by mobile phone usage in South America. Metadata for each call and SMS with identifiers for the other party, time stamps, tower locations and durations were included. The study aimed to predict default based on the information available at the time credit was granted. From the descriptive analysis of the study, the method adopted in the study performs better than those of credit bureau. Findings reveals that use of mobile phone data can score borrowers outside the formal financial system, who cannot score with traditional methods. The data can also predict a wider range of individual characteristics, and could conceivably be used to predict other outcomes such as lifetime customer value, or the social effect of a loan.

Shema (2019) assessed the effectiveness of credit scoring using limited mobile phone data in emerging economies as well as India. This was motivated by the surge of companies providing micro-loans through digital media across many countries; which is fuelled by the need for faster and convenient loans and enabled by the vast adoption of mobile phones and mobile money. Data for the study was based on past airtime charges, dataset with past loans and a combination of both the recharge and loan dataset from April 1st 2017 to March 31st 2018. The study employed supervised learning approach using random forest classifier to predict probability of an applicant's default. The findings of the study demonstrated that we can built credit scoring models for digital lenders with high levels of accuracy by using limited data that may not comprise privacy.

Increased uptake of smartphones among the population have seen increased research on how mobile call and sensor data may be useful in predicting financial risk behaviour of individuals especially those borrowing online from Fintech firms. According to the report by Federalreserve.gov. (2017), more than 50% of the mobile phone users access mobile banking services through connecting their bank accounts to their phones. The report established that credit card data like mobile phone data, can be useful in detecting borrower's mobility and inform lenders about the preferred changes between business categories, thus creating economic profiles that can be helpful in credit scoring. The report utilized data set from over 3 million individuals of a major bank connected with mobile data, and also bills data which included basic bill records and total bills paid each month using smartphones.

Jagtiani and Lemieux (2018) evaluated the role of alternative data in Fintech lending and found increased potential in the use of alternative data which has allowed clients who would have otherwise not accessed loans get lower-priced credit. Upstart which is a constituent company at Fintech uses machine learning to establish employment history, education background, area of study and college, among other modes of alternative data to make decisions on credit. A study by Blechman (2016) found out that majority of applicants in mobile credit lack formal credit histories and this may be attributed to inability to qualify for bank loans, or merely reflect non-functioning or absent credit reporting regime. Linking of mobile credit services with mobile subscription or money account, mobile network operator or even other mobile money services introduces a wealth of crucial consumer data.

A report by Central Bank of Kenya (CBK) in partnership with Kenya National Bureau of Statistics (KNBS) (2017) established that there are now more borrowers using digital means especially smartphones to access credit lists than those seeking loans from traditional banking in Kenya. Eilin, Blumenstock and Robinson (2017) in their study on digital banking argued that digital lenders face credit assessment challenges across the world especially in the developing countries. As a result, they have relied on alternative data to help in building credit score of their borrowers. One key data identified by the study is mobile data such as call detail records, application usage, call and SMS logs and contents. The study argued that these data assist lenders to develop credit score for their borrowers especially in the digital lending where information on borrowers is minimal or unavailable.

2.3.3 Transaction Data

Transactional data comprise of bank accounts which shows the possibilities of what an individual can do. The data is very important as it assist borrowers to prove their identity, and also give an up-to date picture of their financial behaviour. As Fintech market expand, there is a possibility that transactional data is going to remain effective and significant data used by lenders to develop borrowers' credit scoring rates in the market (Westerlund, 2019). Current risk models by various Fintech firms use a combination of individual characteristics, credit behaviour and external ratings (Verkade, 2018). External rating have remained an important aspect of firms especially in the financial services. With an alternative data such as transaction data coming into play, credit assessment of borrowers are provided by external agencies which may comprise of bank activities and loan payment history both by bank and other Fintech firms.

Nordigen (2017) found out that bank account transactions add more value in credit scoring especially among the start-up firms in the financial sector. Before, transactional data were always a document of the traditional banks only. However, with growing Fintech business and the need to develop financial inclusion among the poor and low income areas, the data has been made available for many Fintech firms seek their uses from various banks either upon payments for them or in other ways. According to Nordigen (2017), transactional data may explain a lot about a borrower's financial stability and the ability to repay the borrowed loan on time. Thus, they concluded that with technology that enables Fintech firms to compute these data within a short time, there is a real evidence that transactional data play a big role in establishing credit scoring model in lending decisions. The report concluded that easy access to transaction data means more and more Fintech firms will be able to develop credit rating for their consumers so as to have a competitive edge over their competitors.

Bolagun, Ansary and Agumba (2016) in establishing a possible solution to the challenge of stringent requirements and security for loans among SMEs in Gauteng South Africa, indicate the need for alternative information to determine credit worthiness. The study proposes access to borrowers' trade credit from financial institutions, position at work, location of business, as well as tax number and returns as good pointers for credit accessibility. Verkade (2018) researched on benefits of transaction data on credit scoring for small and medium enterprises. The study established that transaction remain untapped data within major banks. Moreover, it contains useful information that Fintech firms use in determining a borrower's default rate and creditworthiness. The study found out that transaction data enables SMEs to identify more than 50% of their defaults on average and develop effective ways of avoiding such risks in the market.

Payment history especially digital or mobile payments are records of peoples' payment behaviour that illustrates how they pay their debts on time, how effective they use online payment platforms to complete their tractions and the extent to which they adopt financial innovation or digital payment platforms. According to Jayakumar (Jayakumar, 2019), an individual's payment history may be a determinant of his level of credit score. Payment history involves all credit accounts like credit cards and loans. For the Fintech and other financial start-up firms, payment history gives them a snapshot of how borrowers pays their bills, pays their shopping fees as well as rent. These data are essential as they assist lenders in establishing whether the borrowers pay on time, are last minute people or do not pay at all. Payment records that illustrate faster payment may mean a high credit score by Fintech lenders while those with late of missed payment may be deemed defaulters hence having lower credit scoring (Jayakumar, 2019).

Manikandan and Jayakodi (2017) using a questionnaire survey evaluated the adoption of mobile wallet in Chennai City, India and found that the use has been convenient among customers. The study indicates that increased awareness on mobile wallet usage and improved security issues will increase its adoption as alternative mode of online payment. Further, the study indicated awareness and subjective norm as key factors affecting adoption. Thus, higher awareness would improve perception of the benefits of using mobile wallets to manage financial activities. Blechman (2016) evaluated the aspect of mobile credit in Kenya and Tanzania with regard to regulatory challenges on consumer protection, credit report and utilization of customer transactional data. The study found out that mobile credit services have achieved tremendous success in the two financial markets. However, there was need for regulation on the mobile credit consumer protection, credit reporting and use of transactional data.

An evaluation of ten mobile credit services by Hwang and Tellez (2016), nine of which were in sub-Saharan Africa, found out they leverage their services on non-traditional data to decide on lending. Obtaining user digital data is one challenge of credit evaluation and mobile credit providers have to turn it into useful predictor of repayment while evaluating loan applications in setting appropriate credit limits. Lenders thereby devise in-house proprietary software algorithm that collects, sifts and automatically utilizes appropriate weighting to the data to evaluate loan applications without any human review. According to a study by Jayakumar (2019), alternative data sources and algorithms have gained ground in emerging countries and have increased use of the same by mobile apps. The study also found out that the need to establish credible or potential clients for credit is on the rise. When lending facilities access right credit scoring software, they can be able to make crucial decisions on credit requirements of customers

Mobile lending in Kenya has been embraced as an alternative for many low income earners and small entrepreneurs. Ndegwa (2014) looked into the effect of mobile money on non-performing loans of commercial banks in Kenya. Through a descriptive research design, the study established that increased lack of income among Kenyans increases the burden of debt eventually affecting the production or sales of firms. Thus, investing more in technology to establish the credit viability of a client is necessary.

Nzayisenga (2017) evaluated the effect of mobile lending on the financial performance of commercial banks in Kenya through a cross-sectional descriptive survey. The study found out that mobile lending affects the financial performance of Kenyan banks positively and significantly. Thus, policy makers ought to consider mobile lending within their policy making due to technological developments. Further, the study recommended that banks should continuously keep on adopting and utilizing mobile lending in their operations as the number of people using mobile technology is enormous; this will spur economic growth.

Table 2.1 Literature Reviewed

Variable	Author	Title	Methods	Gaps identified	How the study filled the gaps
Social network data	Zhang et al., (2016)	Credit scoring by fusing social media information in online peer-to-peer lending in China	Decision tree	Was conducted in China	Illustrated how social media data is essential in credit scoring in Kenya
	Wei et al., (2015)	How social network data improve credit score	Various models	Did not utilize consumers as the study participants	The study showed the importance of social media data to the consumers As the users of digital loans
	Niu et al., (2019)	Social network data in predicting loan default in peer-to-peer lending	Logistics regression	Did not utilize primary data in showing consumer behavior	Demonstrated the knowledge and understanding of consumers on how digital lenders uses their social media data
	Williams (2016)	How credit scoring firms movements of their borrowers in China & US	Exploratory	The study was conducted in China and US	Described the relationship between social media data and credit score of consumers by digital lenders
Mobile phone data	Bjorkegren & Grissen (2015)	Predicting default of borrowers	Descriptive	The study was not conducted	Used primary data in informing borrowers on the

		using mobile phone usage in South America		in Kenyan context	importance of their mobile phone data in developing their credit score
	Shema (2019)	Effective of credit scoring using mobile phone data in India	Random forest	The study was carried out in India	Demonstrated the need to carry out a similar study using primary data to determine the relationship between the study variables
	Jagtiani & Lemieux (2018)	Alternative data in Fintech lending	Survey	The study did not specifically focus on mobile phone data but provided a general results	This study provide more in-depth on how mobile phone data is essential in improving an applicant's credit score.
	Pritchard (2019)	Financial trouble using call data	Descriptive	The study focused on phone data from the lenders' perspectives	The study focuses on borrowers as the study participants to improve their knowledge on effectiveness of mobile phone data
Transaction data	Nordigen (2017)	How transaction data improves credit scoring	Survey	Was based on the opinion of digital loan providers	Focuses on informing borrowers on the relevance of their transaction records in enhancing their credit score
	Bolagun et al., (2016)	Accessing credit through trade credit from financial institutions in South Africa	Survey	The study was conducted in South Africa	Focuses in describing to the consumers how digital lending firms obtain their transaction data and uses them to develop their credit score

	Verkade (2018)	Benefits of transaction data on credit scoring for SMEs	Survey	The study was conducted on SMEs and not micro SMEs	The study targets individuals and micro businesses
	Blechman (2016)	Aspects of mobile credit in Kenya & Tanzania	Descriptive	Focused on digital lenders and how they use transaction data in building credit score.	Focuses on borrowers to inform them how their transaction data records are used by digital firms in building their credit score

Source: Author (2020)

2.4 Literature Summary and Gaps

From the literature review, various studies have evaluated mobile lending uptake and its effect on commercial bank financial services (Ndegwa, 2014; Murunga, 2017; Nzayisenga, 2017). Other studies have evaluated mobile credit and mobile payments especially in East Africa with respect to its success and technological advancements (Blechman, 2016; Manikandan & Jayakodi, 2017). However, there lacks substantive studies on the concept of mobile lending effectiveness and sustainability especially with respect to client information and its accessibility in Kenya. One key aspect in money lending as outlined by various studies involves stringent measures and requirement for security which affects access to credit among many individuals (Balogun, Ansary, & Agumba, 2016). Nevertheless, this has been attributed by the lack of credit score symmetries or identifying capacity for paying back money given in form of loans. Thus, the use of alternative data plays a pivotal role in establishing the capacity and credit leverage of individuals lacking collateral as security for loans. This study thus, sought to seal the gap by looking into the opportunities of using alternative data within mobile wallets for mobile lending and its sustainability in the Kenyan market.

2.5 Conceptual Framework

A conceptual framework is a model that depicts the relationship between independent variables and a dependent variable of the study. It builds the foundation that illustrates how independent variables affect the dependent variable of the study. This framework was built to assist the study in answering the research aims or questions. For this study, the independent variables were; social network data, mobile phone data and transaction data whereas the dependent variable was credit score for mobile lending on digital wallets. The conceptual framework of the study is presented in figure 2.1.

Independent variables **Dependent variable**

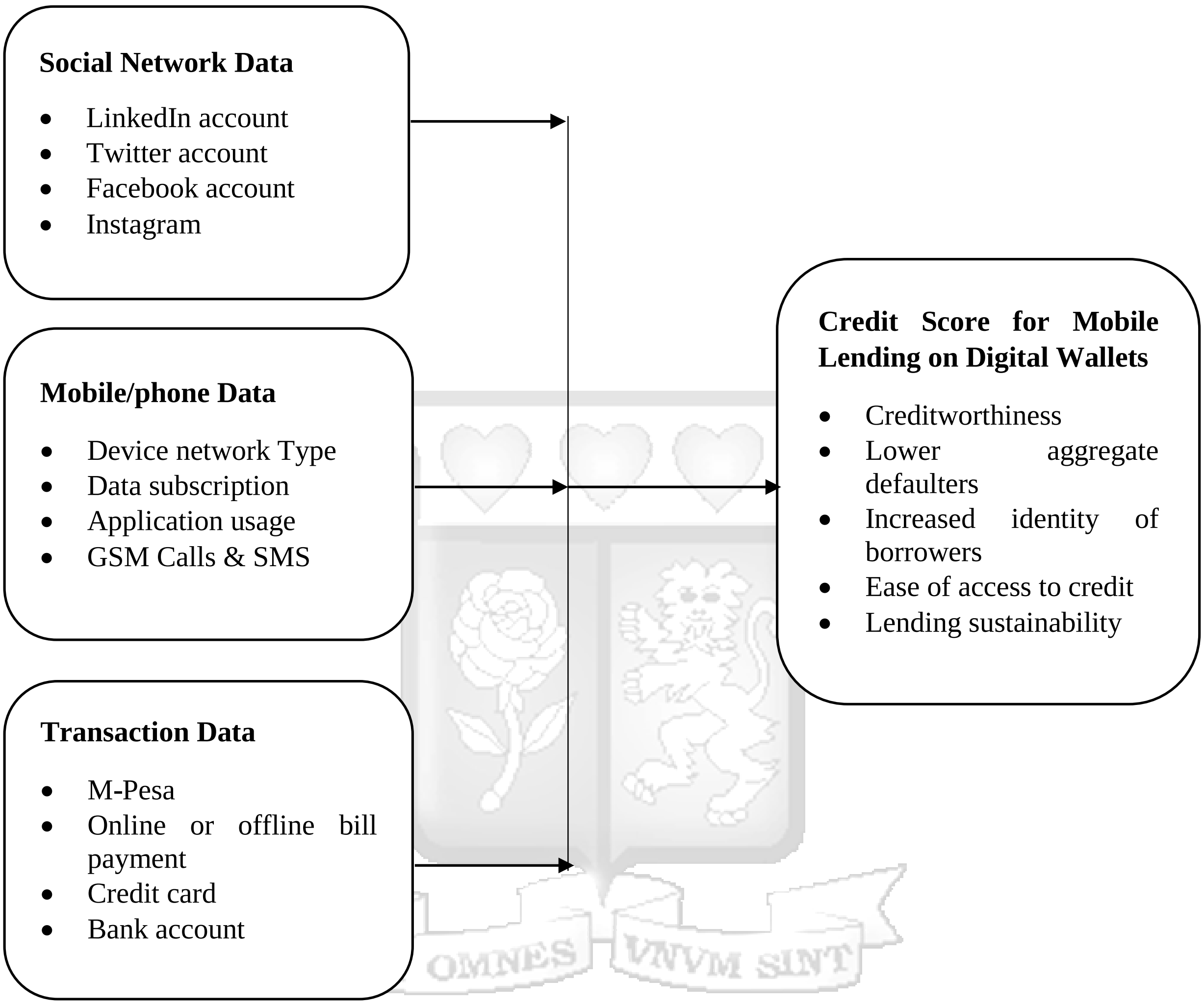

Figure 2.1 Conceptual Framework

Source: Author (2020)

2.6 Operationalization of Variables

The operationalization of the variables is a table that highlights the constructs of a research's variables into observable and measurable units. For the independent and dependent variables of the study, a rating scale of 1-5 was used to measure the constructs of the variables. Likert Scale was adopted as it assists in quantifying the data so that it can be easily coded and analysed. The following scale was adopted (5-strongly agree (SA), 4-agree (A), 3-neutral (N), 2-disagree (D) and 1-strongly disagree (SD). The operationalization of the variables therefore is summarized as follows.

Table 2.2 Operationalization of Variables

Variables	Variable Type	Theory	Indicators	Rating scale	Analysis	Author
Social Network Data	Independent	Financial intermediation	Obtaining reviews on Fintech, very useful in business promotion, Data mining to know type of social network.	Likert scale	Descriptive and inferential statistics	(Chui, 2013) (Williams, 2016) (Majumder, 2019)
Mobile phone Data	Independent	Diffusion of innovation	Checking long call hours, usage of apps on phone, daily routine habits of calls and texts, checking contacts to see contacts credit score	Likert scale	Descriptive and inferential statistics	(Huang, 2019) (Pritchard, 2019) (Agarwal, Lin, Chen, & Singh, 2018)
Transaction Data	Independent	Diffusion of innovation	Frequent online or offline payments, frequent use of credit cards, other forms of payments through mobile apps, how fast individual pay bills	Likert scale	Descriptive and inferential statistics	(Westerlund, 2019) (Nordigen, 2017) (Verkade, 2018)
Credit Score for Mobile Lending Wallets	Dependent		Need to establish credit worthiness, need to have lower aggregate loan defaulters, identify lenders and their close networks, lending sustainability	Likert scale	Descriptive and inferential statistics	(Nzayisenga, 2017) (Karanja, Mwangi, & Nyakarimi, 2014)

Source: Author (2020)

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter demonstrates the methodologies that the study used to achieve the research aims. First, it demonstrates the research design to be adopted by the study. It then states the population of the study; and the sampling method that was adopted to get the appropriate sample size of the study. Third, the chapter explains the method that was used to collect data from the respondents and the procedure used. It also highlights the data analysis technique that was used to analyse the data gathered from the field, how it was coded and interpreted to make conclusions. Lastly, the chapter explains the research quality; both validity and reliability as well as ethical considerations in the research study.

3.2 Research Philosophy

Research philosophy act as the guiding principles and beliefs that directs the objectives of the study. It presents the credibility of the study, a process of convincing others on the suitability and the need to carry out the study. There are a number of research philosophies such as ontology, epistemology and positivism. Ontology describes what things are while epistemology is about how we know things. Positivism suggest that true knowledge is attained through factual accounts of analysis objectively via scientific methods of analysis. This study therefore adopted logical positivism as the ideal research philosophy. The philosophy is based on logical reasoning in order to improve knowledge and understanding of the phenomenon objectively through scientific process or analysis (Saunders, Lewis, & Thornhill, 2007).

3.3 Research Design

A research design is a study template that illustrates the plans and structure that guided the study towards attaining its aims or objectives so as to answer the research problem (Mugenda & Mugenda, 2013). It is a statistical framework highlighting the research approach that was adopted for the examination of the study phenomenon. Thus, the goal of this study was to describe how alternative data may be useful in achieving credit scoring for mobile lending on digital wallets. Since the study uses quantitative data, descriptive research design or approach was adopted. The advantage of this design over others is that it describes the relationship between factor variables of the study; for example, how alternative data relates to credit score for mobile lending on digital wallets. The design was also useful as it provided a detailed information regarding the relationship of the independent and dependent variables of the study.

3.4 Population and Sampling

3.4.1 Target Population

Population of a study refers to the total observation or persons or objects that the study targeted to aid in providing critical information that was effectively used to answer the research questions. Population of the study should have same characteristics so as data obtained can be essential for study analysis. The study was based on the mobile lending application users. Thus, the target respondents of the study were individuals and informal micro enterprise users of mobile loan applications. According to WAPI Capital report, close to 20.1 million Kenyans have an active mobile loan accounts with few being multiple loan takers (WAPI Capital, 2018).

The study developed inclusion and exclusion criteria for the target population. To be included in the study, the target population had to meet two conditions; one was to be a registered user or subscriber of mobile lending application with over two years active account and second, to be a frequent user of mobile loan applications where you either take loans for businesses purposes or activities related to informal micro businesses.

3.4.2 Sampling Technique and Sample Size

Sampling technique refers to mechanism which the study used to pick the appropriate sample size of the study. Sample refers to the total portion of the population picked to represent the entire population in the study. Due to large population, researchers always advise for a smaller representation to be chosen so as to reduce time and cost of the study (Creswell & Poth, 2017). First for this study, the sample population comprised of individuals and informal micro enterprises. The study adopted two sampling techniques; scientific and non-probability. Due to the large population size of the study, this study adopted Cochran (1963) formula for calculating a sample for proportions, where; n_o is the sample size, Z^2 is confidence interval (95% = 1.96), e is the desired level of precision (5%), p is the estimated proportion of an attribute that is present in the population (0.5) while q is 1-p (1-0.5). The value for Z was estimated from statistical tables which contains the area under the normal curve. The resulting sample size of the study was demonstrated as follows;

$$n_0 = \frac{Z^2pq}{e^2} = \frac{(1.96)^2(0.5)(0.5)}{(0.05)^2} = 385\ respondents$$

The study then used stratified technique to classify research participants into groups of four; M-Pesa/Mshwari/KCB-Mpesa, Tala, Branch and others. Secondly, the study adopted both purposive and convenience non-probability sampling methods. Purposive sampling method was used to determine appropriate number of research participants in each group identified in the study (table 3.1). Thereafter, convenience sampling technique was adopted to aid in data collection based on the availability and willingness of research participants to participate in the study as shown in table 3.1.

Table 3.1 Sampling Frame

Mobile lending providers	Mobile loan subscribers	Sample Size
M-Pesa/M-Shwari/KCB-MPesa	Individual	100
	Informal micro enterprises	68
Total		**168 (43.6%)**
Tala	Individual	65
	Informal micro enterprises	30
Total		**95 (24.7%)**
Branch	Individual	53
	Informal micro enterprises	15
Total		**68 (17.7%)**
Others	Individual	39
	Informal micro enterprises	15
Total		**54 (14.0%)**
Total sample size		**385**

Source: Author (2020)

Further, the study separated the study participants into individuals and informal micro enterprises. This idea was formed by the need to establish the purposes of taking loans from digital lenders either for personal use or for small businesses. The idea was formed by the researcher's opinion to ensure that the objective of the study remain relevant from both individual borrowers who take loan for personal use, and those individuals who take loan to start or manage their informal micro businesses in Nairobi.

3.5 Data Collection Techniques and Procedures

Data collection methods refers to the instruments that were adopted to aid in gathering the appropriate data for the study as well as the process that was followed by the researcher (Neuman, 2013). Quantitative data was used. For this reason, the study designed structured questionnaire to aid in data collection. The advantage of structured questionnaire is that the researcher designs questions based on the objectives of the study and request the respondents to respond to the questions based on their level or degree of agreement. Thus, the structured questionnaires were designed based on Likert scale type as the data collection tools. Another advantage of structured questionnaire as a data collection tool is that it saves time and gives the respondents ample time to read, understand and respond to the questions based on the guidelines that were given (Cooper & Schindler, 2014).

Moreover, since the study uses quantitative data, self-administered questionnaire were used. To effectively collect accurate and reliable information from the research participants within the study period, the study relied on the help of research assistants. Two research assistants were first trained on key research and communication skills and the general objectives of the study. The researcher together with the research assistants then went through the questionnaire to read, discuss and understand the research questions for easy explanation to the participants should they raise any question or seek further assistance. Due to the nature of research participants, this study adopted face to face administration of data collection procedure. This involved approaching individuals and seeking for their consent to respond to the research questions. The same strategy was applied to the informal micro enterprises. The researcher created a friendly environment by informing the respondents the purpose of the study.

3.6 Data Analysis and Presentations

This section of the chapter of the study discusses the techniques that were used to analyse data. Data analysis refers to the process of editing and coding data to make it a useful information that can be easily analysed to make interpretation and conclusions of research objectives. Once data was gathered from the respondents using questionnaires, they were verified to determine consistency, errors and completeness. The data were then coded in excel worksheet before being transferred to Statistical Package for Social Sciences (SPSS V. 22.0). Descriptive analysis through mean, median and standard deviation was used to describe the population. In addition, descriptive analysis assisted in describing the data for the study and established the participants' extent of agreement with a number of statements or measurements included under each variable of the study.

The purpose of the study was to describe and establish the relationship between dependent and multiple independent variables included and the causal effects. To objectively address the research objectives, a multiple regression analysis (multivariate) method was adopted in the study. Multiple regression uses multiple independent variables with each controlling for the other (Saunders, Lewis, & Thornhill, 2007). This method was utilized to describe the relationship between alternative data types and credit score for mobile lending on digital wallets. It included an error term, whereby response variable were expressed as a combination of explanatory factors, and the unknown parameters estimated using observed values of the dependent and independent variables. Additionally, the study used multiple linear regression to attempt and model the relationship between explanatory variables and response variable by fitting a linear equation of the observed data.

SPSS (Version 22.0) was used to conduct the analysis. Credit score for mobile lending on digital wallet in Kenya (Y) was regressed against three (3) variables; social network data (X_1), mobile phone data (X_2), and transaction data (X_3). In the equation, β_0 represented coefficient of intercept or simply constant whereas $\beta_1 - \beta_n$ represented the coefficient of predictor factors or variables and ε is an error term.

$$\gamma = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon$$

The study model was estimated using ordinary least square regression method at 95% confidence interval and 5% significance level. Correlation analysis was estimated to measure the strength of linear relationship between independent and dependent variables. Goodness of fit of the regression model was estimated using coefficient of determination (R^2) as well as the analysis of variance (ANOVA) to indicate the direct and strength of relationship of the study variables.

However, before inferential analysis, principal component analysis (PCA) which is a statistical tool used to emphasize variation and bring out strong patterns of relationship in a dataset was conducted, to make data easy to explore and visualize. The PCA described the dimensionality of the study's data set. It explains how the dataset can be transformed into a smaller one that stills contains important information in the large data set of the study. Additionally, diagnostic tests such as serial autocorrelation and multicollinearity were also determined prior to inferential analysis.

3.6.1 Diagnostic Tests Results

One of the linear regression assumptions is that data for the study should be linear and normal. Therefore, before establishing the model fit of the study model, the study estimated serial correlation and multicollinearity test of the study.

Table 3.2 Serial Autocorrelation

Model	Std. Error of the Estimate	Durbin-Watson
1	.4905	1.776

a. Predictors: (Constant): Social network data, Mobile phone data, Transaction data
b. Dependent Variable: Credit Score

Source: Field Data (2020)

Using Durbin-Watson test, the study tested whether residuals of the study are auto correlated. Findings in table 3.2 reveals that Durbin-Watson test result was 1.776 which is between the autocorrelation rule of thumb value of 1.5 and 2.5. Therefore, this implies that there is no problem of serial autocorrelation in the residuals of the study model.

Table 3.3 Multicollinearity

Coefficients[a]

Model		Collinearity Statistics	
		Tolerance	VIF
1	Social network data	.813	1.230
	Mobile phone data	.798	1.253
	Transaction data	.903	1.107

a. Dependent Variable: Credit Score

Source: Field Data (2020)

Variance Inflation Factor (VIF) was used to test for multicollinearity among the independent variables of the study. In the model fit of the study, independent variables should not have correlation between them. A VIF below 4 indicate that there is no correlation between the independent variables of the study. Results in table 3.3 indicates that social network data, mobile phone data and transaction data had a VIF value of 1.230, 1.253 and 1.107 respectively which were all below 4. This indicate that there was no correlation between independent variables of the study. The presence of multicollinearity can cause serious problems with estimation of regression coefficients and their interpretation (Oke, Akinkunni, & Etebefia, 2019).

3.7 Research Quality

Research quality aimed to address the validity and reliability of the research instruments. Before the questionnaires were administered to the target population, pilot study was conducted. This aimed to establish errors and weaknesses of the developed research instruments so as to ensure that data collected were fit for answering the research questions. A good pilot study should be less than or equals to 10% of the sample size. Therefore, 2% of the sample size was used for the pilot study; approximately 8 respondents participated. This population was not part of the real target population of the study. However, was purposively selected to participate in the study. They included 5 individuals and 3 informal micro enterprises in Nairobi's informal settlements. The findings from the pilot study was used to improve measurement constructs of study variables in the questionnaire tool.

3.7.1 Validity of Research Instrument

This is the extent to which self-administered questionnaire for data collection would truly provide the accurate information needed for the study (Sekaran & Bougie, 2016). Therefore for a research instrument to be valid, it must be simple and accurate as well as research objective oriented for it to effectively gather the intended data for the research study. Validity seeks to ensure that the questions developed in the study are aligned to the objective of the study. Thus, content validity was used. It is where the researcher shared the developed questionnaire with experts such as supervisor so as to get their opinions. Changes were made where possible until the instrument became accurate (Creswell & Poth, 2017).

3.7.2 Reliability of Research Instrument

Reliability is the degree to which the questionnaire could give the same results when used over time. A good questionnaire therefore is said to be consistent if it could give similar results when used several times to gather data for a similar study at different intervals (Saunders, Lewis, & Thornhill, 2007). One way that the study used to determine the consistency of the study was through Cronbach's alpha. This measure shows the degree to which a set of test items included under each variable of the study in the questionnaire were considered reliable when they have a value of 0.7 and above (Neuman, 2013) as shown in table 3.4

Table 3.4 Reliability Findings

Study Variables	Cronbach's alpha	Number of Items
Social network data	.703	7
Mobile phone data	.716	7
Transaction data	.709	7
Credit score for mobile lending wallets	.711	6

Source: Field Data (2020)

3.8 Research Ethical Considerations

The study was undertaken within the stipulated research standards and guidelines. It first obtained an ethical approval letter from Ethics Committee of Strathmore University followed by the NACOSTI research permit from the Ministry of Education. The researcher then proceeded to the field of study. The ethical letters obtained were attached to the consent letter which described the purpose of the study and sought for consent of the respondents.

CHAPTER FOUR

DATA ANALYSIS AND PRESENTATION OF RESEARCH FINDINGS

4.1 Introduction

This chapter presents the findings of the study as analysed using SPSS version 23.0. The study sought to describe the role of alternative data in accurately determining credit score for mobile lending on digital wallets in Kenya. Descriptive, principal component analysis (PCA) and inferential analysis were conducted in line with the research objectives. In summary, this chapter presents the findings of the study on response rate, demographic, descriptive, PCA of combined dataset and inferential analysis.

4.2 Response Rate

Based on the sample size of the study, a total of 385 questionnaires were printed and administered face to face to the respondents. A total of 267 questionnaires were duly filled and returned for analysis. This represented 69.3% response rate for the study as shown in table 4.1. This response rate was considered acceptable to make study inferences. A response rate of 50% is considered adequate, 60% is good while 70% and above is very good (Mugenda & Mugenda, 2010; 2013). Based on this assertion, the response rate of 69.3% of this study was therefore good. Moreover, the recorded response rate of 69.3% can be attributed to the data collection challenges especially identifying informal micro businesses and individuals since at the time of data collection process, coronavirus also known as COVID-19 disease had been declared pandemic and the government of Kenya had restricted movements of people and isolation in Nairobi.

Table 4.1 Response Rate

Response category	Target sample size	Response rate
Returned questionnaires	267	76%
Un-Returned questionnaires	83	24%
Total	350	100%

Respondents by category	Frequency	Percentage
Individuals	172	64.4%
Informal micro businesses	65	35.6%
Total	267	100%

Source: Field Data (2020)

Additionally, of the 267 (69.3%) of the participants who dully filled the questionnaires, the study established that 172 (64.4%) were individuals whereas 95 (35.6%) were informal micro businesses in areas of Nairobi.

4.3 Demographic Findings

The study presents the results on the general information of the respondents. This includes gender, age category, level of education, sector of business, which mobile lending apps they use and status as an active mobile loan app user, duration of loan repayment and rating of usefulness of credit score by Fintech firms.

4.3.1 Gender, Age Category and Education Level

The descriptive statistics of the study demonstrated that out of the 267 participants, majority were male 176 (65.9%), as shown in table 4.2. The findings reveal that the two genders were adequately represented in the study since there was no gender which was more than the two-thirds. However, statistical analysis reveal that male gender could be dominating the mobile lending platform in Kenya.

Table 4.2 Demographic Information of the Respondents

Demographic Summary Findings of the Respondents

Demographics	Category	Frequency	Percent (%)	Cumulative Percent
Gender	Male	176	65.9	65.9
	Female	91	34.1	100.0
	Total	267	100.0	
Age category	<20 years	18	6.7	6.7
	21 – 30 years	83	31.1	37.8
	31 – 40 years	108	40.4	78.3
	41 – 50 years	41	15.4	93.6
	51 – 60 years	14	5.2	98.9
	Above 60 years	3	1.1	100.00
	Total	267	100.0	
Education	Undergraduate	64	24.1	24.1
	Graduate	63	23.7	47.7
	Post-graduate	13	4.9	52.6
	Other	127	47.4	100.0
	Total	267	100.0	

Source: Field Data (2020)

Table 4.2 also presents the results of how respondents were distributed as per age groups. Majority of the respondents 108 (40.4%) were in the age category of 31 – 40 years followed closely by 83 (31.1%) who were in the age category of 21 – 30 years. In addition, 41 (15.4%) were in the age category of 41 – 50 years, 18 (6.7%) were below 20 years, 14 (5.2%) were in the category of 51 – 60 years while less than 2% were above 60 years. From the findings, the study can deduce that most active age groups involved in digital lending for mobile wallets in Kenya are youths below the age of 40 years. Specifically, individuals in the age category of 31 – 40 years and 20 – 30 years are the most involved in mobile lending for digital wallets activities respectively. There is increase of individuals involved in digital lending once they attain the age of 20 years.

Results in table 4.2 further shows that majority of the respondents 127 (47.4%) had other levels of education. Also, 64 (24.1%) and 63 (23.7%) of respondents had undergraduate and graduate level of education respectively while only 13 (4.9%) of the respondents had post-graduate level of education. Therefore, based on the education findings, the study managed to gather diverse information concerning respondents' level of knowledge and understanding on alternative data and mobile lending on digital wallets. Additionally, the assumption from the findings is that majority of the respondents involved in mobile lending on digital wallets may have diploma, certificate or professional course qualifications as other forms of education

4.3.2 Sector or Business and Mobile lending Demographics

Moreover, the study also assessed which sector best describes business idea in the informal sector. 94 (35.2%) and 90 (33.7%) of the respondents categorises trading and service business as their preferred business ideas respectively, in the informal sector as shown in table 4.3. From these findings, the study deduce that most individuals borrow money through their phones to start their small businesses in trading and service sector. However, the study did not categorically establish which type of trading or service businesses these individuals are involved in. Additionally, descriptive statistics indicated 53 (19.9%) are in agribusiness while 20 (7.5%) and 10 (3.7%) indicated manufacturing and other businesses as their preferred business sectors respectively. Therefore as in indicated in table 4.3, majority of the respondents preferred trading and service sectors. That is, they would use mobile lending services to finance their business idea in these informal sectors of the economy.

Table 4.3 Sector or Business and Mobile lending Demographics

Mobile Lending Demographics Summary Findings

Demographics	Category	Frequency	Percent (%)	Cumulative Percent
Sector of business idea	Trading	94	35.2	35.2
	Service	90	33.7	68.9
	Agribusiness	53	19.9	88.8
	Manufacturing	20	7.5	96.3
	Others	10	3.7	100.0
	Total	267	100.0	
Mobile loan user app	Tala	79	29.6	29.6
	Branch	68	25.6	55.1
	Safaricom app	62	23.2	78.3
	Others	7	2.6	80.9
	More than one	51	19.1	100.0
	Total	267	100.0	
Active loan user	Yes	239	89.5	89.5
	No	28	10.5	100.0
	Total	267	100.0	
Loan repayment time	Within a week	28	10.5	10.5
	Two-three weeks	66	24.7	35.2
	Four weeks	121	45.3	80.5
	Above four weeks	52	19.5	100.0
	Total	267	100.0	
Rate of usefulness of credit score	Very high	56	21.0	21.0
	High	58	21.7	42.7
	Moderate	85	31.8	74.5
	Low	68	25.5	100.0
	Total	267	100.0	

Source: Author (2020)

The study further established the preferred mobile lending apps for the users. Results in table 4.3 reveals that almost all the participants preferred using the mobile lending apps identified in the study. That is, Tala mobile was the most downloaded mobile app by 79 (29.6%) followed closely by Branch mobile app at 68 (25.6%). Safaricom app which has both KCB MPESA and MSHWARI came third at 62 (23.2%). However, most respondents noted that since MPESA services already has the services internally, they do not see the reason for downloading the Safaricom app again; unless they are seeking for other services. 7 (2%) of the respondents use other mobile lending apps. Also, 51 (19.1%) of the respondents stated that they use more than one mobile lending app.

The study also sought to determine whether respondents were active users of mobile lending apps. As shown in table 4.3, majority of the respondents 239 (89.5%) said that they are not only active users of mobile loan apps but also their mobile lending apps are active as well. This imply that these users occasionally use mobile lending on digital wallets either for personal use or for their business activities. However, a minority of the respondents 28 (10.5%) stated that they are not active users of mobile lending apps. That is, they rarely use mobile lending apps; they mostly use it as an emergency source of funds. In addition, findings reveal that it take four weeks for majority121 (45.3%) of the respondents to pay back their loan; 66 (24.7%) and 52 (19.5%) take between two to three weeks and above four weeks respectively to settle their loan. Based on these findings in table 4.3 , the study can deduce that most mobile lending on digital wallets have preferred loan repayment plan or duration of 4 weeks, approximately one month. Digital consumers are therefore supposed to repay their digital loan within 4 weeks of borrowing. In rating the usefulness of credit score by Fintech firms, 85 (31.8%) of the respondents indicated moderate rating, 58 (21.7%) and 56 (21%) indicated very high and high rating respectively while 68 (25.5%) rated it low. Thus, there was divergent views regarding rating of usefulness of credit score by Fintech firms.

4.4 Descriptive Findings of Study Variables

This section of the study presents findings on measurements of study variables as indicated by the respondents. It aimed to present the views or reactions of the respondents regarding the predetermined statements under each study variables using a Likert-Scale. Thus, mean and standard deviation are used to explain the study findings. Mean above 3.0 indicated that respondents agree while below 3.0 indicated that respondents did not agree.

4.4.1 Social Network Data

This objective sought to determine whether respondents understand the concept of social network data and its usefulness by mobile loan app firms in building credit score of individuals who seek for mobile lending services. The findings are presented in table 4.4.

This objective of the study looked into how Fintech firms use social media accounts such as twitter, LinkedIn, Instagram and Facebook among others in building credit score for individual consumers. Taking into account the views of the respondents, table 4.4 presents a composite mean of 2.743. This clearly indicate that respondents did not agree on the usefulness of social network data in building their credit score. Whether the information on their social media accounts are genuine had a mean of 2.14, suggesting that most of the respondents disagreed with the statement.

Table 4.4 Descriptive Findings on Social Network Data

	Statistics			
Statements	Obs	Mean	Median	Std. Dev
Are the information on your social media accounts genuine ones?	267	2.14	2.00	1.131
A part from Facebook, Twitter, and Instagram, I am registered in other social media accounts	267	3.12	3.00	1.162
Do you spend too much of your time on social media, even at night?	267	2.85	3.00	1.186
Do you often communicate to your family using other social media accounts such as WhatsApp?	267	2.07	2.00	1.105
Do you rely on your social media accounts to know the breaking news?	267	2.94	3.00	1.069
Do you find using social media accounts easier and cheaper than phone calls?	267	2.74	3.00	1.172
Do you have an idea that your social media accounts should reflect who you are?	267	3.35	3.00	1.347
Composite mean		**2.743**		

Source: Field Data (2020)

The assumption on this finding is that some respondents may be having false information on their social accounts, thus do not understand how this information is critical in building their credit score. While Williams (2016) indicated how Fintech firms in China and US uses social network data to build credit score for individuals, it is evident that locally, consumers are still not knowledgeable on the usefulness of social network in building their credit score.

4.4.2 Mobile Phone Data

In this section, the study presents descriptive findings on the level of understanding of consumers on how Fintech firms use contents of their phones such as call logs, text messages, data subscriptions and downloaded application usage in building their credit score. Findings are presented in table 4.5 based on the level of agreements of each statement.

Table 4.5 Descriptive Findings on Mobile Phone Data

	Statistics			
Statements	Obs	Mean	Median	Std. Dev
Would you agree that you have subscribed to daily mobile data, calls and messages?	267	2.19	2.00	1.079
Do you purchase expensive mobile data on a weekly/monthly basis due to online shopping?	267	3.10	3.00	1.159
All your mobile apps are always active since you use all them on a daily basis	267	2.81	3.00	1.252
I can confirm that since the introduction of chat apps such as WhatsApp I have reduced the number of daily phone calls	267	2.36	2.00	1.181
I do make long calls if I get an opportunity of calling my friends or any other calls	267	2.84	3.00	1.112
I can confirm that I observe both wording and punctuations in either short or long messages	267	2.16	3.00	1.227
I can confirm that I spend too much on mobile data so as to use available mobile apps	267	2.81	3.00	1.231
Composite mean		**2.753**		

Source: Field Data (2020)

As indicated in table 4.5 the study explored respondents' perspectives on the measurements of mobile phone data as an alternative data in determining individual credit score. The study established a composite mean of 2.753, indicating that they did not agree on the relationship between mobile phone data and credit score for mobile lending on digital wallets. Would you agree that you have subscribed to daily mobile data, calls and messages had a mean of 2.19 while I can confirm that since the introduction of mobile chats such as WhatsApp I have reduced the number of daily phone calls had a mean of 2.36. All these indicate the level of disagreements of respondents with these statements. Therefore, there is a disagreement with the findings of Huang (2019) whose study concluded that how individual organizes his or her contacts and how they structure their short messages can be helpful as data points in credit score model. This could be attributed to lack of awareness on the usefulness of these information among respondents as established in the current study by a mean below 3.0. However, respondents also agreed that they observe both wording and punctuations in either short or long messages with a mean of 3.16 as they also purchase expensive mobile data on a weekly/monthly basis due to online shopping which had a mean of 3.10.

4.4.3 Transaction Data

The third and final objective of the study was to determine the relationship between transaction data and credit score for mobile lending on digital wallets. In this section however, descriptive findings are presented to illustrate respondents' level of agreement with measurements of transaction data variable as created in the study. Findings were presented in table 4.6.

Table 4.6 Descriptive Findings on Transaction Data

	Statistics			
Statements	Obs	Mean	Median	Std. Dev
In the past, have you find it convenient paying for your utility bills using M-Pesa?	267	2.07	2.00	1.093
I prefer making cash withdrawals from the bank using my phone	267	2.16	2.00	.935
I can confirm that I have more than two debit/credit cards which are all connected to my phone number	267	2.87	3.00	1.240
I prefer paying for goods and services using phone at all time irrespective of their value or quantity	267	2.95	3.00	1.255
I always leave a small amount in both my bank account as well as my MPESA and debit card accounts	267	2.19	2.00	.940
I always prefer making my household subscription payments on time using phone	267	3.03	3.00	1.375
I frequently receive my bank/MPESA monthly transaction statements on my phone	267	2.93	2.00	1.368
Composite mean		**2.599**		

Source: Field Data (2020)

Table 4.6 presents findings on transaction data. Overall measurements composite mean findings of 2.599 reveals that respondents have little knowledge on the relationship between transaction data and credit score. This may also reveal their level of disagreements where for instance, whether in the past you have find it convenient paying for utility bills using MPESA have a mean of 2.07, I prefer paying for goods and services using phone at all times irrespective of their value or quantity have a mean of 2.95. However, respondents also agreed that they always prefer making their household subscription payments on time using phone with a mean of 3.03. Thus, the descriptive findings of the current study is in agreement with the previous findings of Verkade (2018) whose study argue that transaction data remain untapped within major banks even though it contains useful information that Fintech firms use in determining a borrower's default rate and credit worthiness.

4.4.4 Credit Score

This is the dependent variable of the study. The study sought to obtain perception of respondents on credit score for mobile lending on digital wallets based on their level of agreements with each measurement's constructs. The findings are presented in table 4.7.

Table 4.7 Descriptive Findings on Credit Score for Mobile Lending on Digital Wallets

	Statistics			
Statements	Obs	Mean	Median	Std. Dev
I can confirm that I prefer taking loan on mobile lending apps since they provide me with faster processing of loan application?	267	2.00	2.00	1.067
I agree that all the information in all my social network accounts are accurate and resemble my personality?	267	2.73	3.00	1.050
Since I started using online lending apps, I have found it easy to take loan in other lending apps which I had not used before?	267	2.66	2.00	1.201
I can confirm that mobile lending apps ask me certain questions before giving out loan, giving ideas on how to effectively use the money?	267	2.55	2.00	1.137
How often have you defaulted your loan and has it reduced your loan application amount in other mobile loan apps?	267	3.55	4.00	1.220
Have found lending apps easy to use and very reliable than asking for a friend or a family to give me a small loan.	267	2.57	2.00	1.220
Composite mean		2.675		

Source: Field Data (2020)

Credit score of each individual borrower is very important for every Fintech firm. As presented in table 4.7, firms develop credit score to establish credit worthiness of their consumers, need to have lower aggregate loan defaulters and to have lending sustainability. The established mean of 2.675 clearly indicate that majority of the respondents may not be aware of their credit score which Fintech firms use when providing them with mobile loans. It represents their level of disagreement. Moreover, respondents disagreed that mobile lending apps ask certain questions when providing loans with a mean of 2.55 while also disagreeing that they have found lending apps easy to use and very reliable than asking for a friend or a family to give a small loan with a mean of 2.57. However, majority of the respondents also agreed that they have often defaulted their loans and this has reduced their loan application amount limit in other mobile loan apps as well with a mean of 3.55. This is in line with the previous study by Karanja et al (2014) that due to high growing cases of mobile loan defaulters, mobile lending for digital wallets are developing credit score for individual consumers to establish their credit worthiness and trustworthiness in the market.

4.5 Principal Component Analysis

Before the inferential analysis was conducted, the study performed principal component analysis (PCA). PCA is a statistical tool used to emphasize variation and bring out strong patterns of relationship in a dataset. It is usually used to make data easy to explore and visualize. The PCA described the dimensionality of the study's data set. It explains how the dataset can be transformed into a smaller one that stills contains important information in the large data set of the study. For this study, it was used to describe which measurement constructs under each variable of the study, closely relate to study variables for easy analysis. Therefore, the analysis was conducted and findings under each variable components are presented in ascending order.

The PCA technique was used to describe dimensions of alternative data and credit score for mobile lending on digital wallets. The preliminary PCA resulted in Kaiser-Meyer-Olkin (KMO) measure of adequacy test statistics of .702 which was considered adequate (Tabachnick & Fidell, 2007). Bartlett's test of Sphericity resulted in a significant p-value of .000 < .05. The un-rotated result was conducted using 27 components out of which 10 components explained 59.371% of the variations leaving 40.529% of the variations to be explained by the other 17 components (table 8). A varimax with Kaiser Normalization rotation method indicated a four component structure (table 8). Component one (1), represented factor one (1) which is social network data dimension, and was illustrated using 7 items including; do you find using social media accounts easier and cheaper than phone calls?, and had the highest factor loading of .682, followed by "do you have an idea that your social media accounts should reflect who you are?" (.632), "do you spend too much of your time on social media, even at night?" (.625). The second component (2) represented the factor mobile phone data (2) dimension and was exceedingly expounded by "I can confirm that I spend too much on mobile data so as to use available mobile apps" with a factor loading of .659, "I do make long calls if I get opportunity of calling my friends of any other calls" (.629), "all your mobile apps are always active since you use all of them on a daily basis" (.626) (table 8).

Table 4.8 Rotated Component Matrix of the Combined Data Set

Item	Component 1	2	3	4	Factor
Do you find using social media accounts easier and cheaper than phone calls?	.682				
Do you have an idea that your social media accounts should reflect who you are?	.632				
Do you spend too much of your time on social media, even at night?	.625				1
A part from Facebook, Twitter, and Instagram, I am registered in other social media accounts	.592				
Are the information on your social media accounts genuine ones?	.582				
Do you often communicate to your family using other social media accounts such as WhatsApp?	.565				
Do you rely on your social media accounts to know the breaking news?	.495				
I can confirm that I spend too much on mobile data so as to use available mobile apps		.659			
I do make long calls if I get an opportunity of calling my friends or any other calls		.629			2
All your mobile apps are always active since you use all them on a daily basis		.626			
I can confirm that I observe both wording and punctuations in either short or long messages		.603			
Would you agree that you have subscribed to daily mobile data, calls and messages?		.458			
Do you purchase expensive mobile data on a weekly/monthly basis due to online shopping?		.458			
I can confirm that since the introduction of chat apps such as WhatsApp I have reduced the number of daily phone calls		.414			
I always leave a small amount in both my bank account as well as my MPESA and debit card accounts			.813		
I prefer making cash withdrawals from the bank using my phone			.708		
I always prefer making my household subscription payments on time using phone			.635		3
I can confirm that I have more than two debit/credit cards which are all connected to my phone number			.619		
In the past, have you find it convenient paying for your utility bills using M-Pesa?			.597		
I frequently receive my bank/MPESA monthly transaction statements on my phone			.575		
I prefer paying for goods and services using phone at all time irrespective of their value or quantity			.571		
I can confirm that I prefer taking loan on mobile lending apps since they provide me with faster processing of loan application?				.660	
I agree that all the information in all my social network accounts are accurate and resemble my personality?				.621	4
I can confirm that mobile lending apps ask me certain questions before giving out loan, giving ideas on how to effectively use the money?				.593	
Have found lending apps easy to use and very reliable than asking for a friend or a family to give me a small loan.				.548	
Since I started using online lending apps, I have found it easy to take loan in other lending apps which I had not used before?				.540	
How often have you defaulted your loan and has it reduced your loan application amount in other mobile loan apps?				.529	

Extraction Method: Principal Component Analysis

Source: Field Data (2020)

The third component (3) represented the factor transaction data (3). Variations in the transaction data was expressed to a high degree by I always leave a small amount in both my bank account as well as my MPESA and debit card accounts, having factor loading of .813, followed by "I prefer making cash withdrawals from the bank using my phone" (.708), and "I always prefer making my household subscription payments on time using phone" (.635). The fourth component (4) represented credit score for mobile lending on digital wallets, which was the fourth factor (4) and the dependent variable of the study (table 8). The construct "I can confirm that I prefer taking loan on mobile lending apps since they provide me with faster processing of loan applications" had the highest factor loading of .660, while the construct "I agree that all the information in all my social network accounts are accurate and resemble my personality" had a factor loading of .621. The study therefore established that all the dimensions or constructs under each component of the study as indicated by PCA, were reliable in answering the research objectives; except for one construct under social network data and mobile phone data each which had factor loading < .5.

4.6 Inferential Analysis

Inferential analysis sought to provide essential information in answering the research objectives of the study. Correlation and regression analyses were conducted to explain the relationship between independent variables and dependent variables of the study. The analyses were expressed together on each independent variables of the study.

Correlation analysis measures or evaluates the strength of the relationship between two variables of the study. A high correlation indicates that the variables have a strong relationship with each other, while a weak correlation means that the variables are hardly related. For this study, correlation analysis was carried out to determine the strength of relationship between independent variables of the study (social network data, mobile phone data and transaction data) and dependent variable (credit score for mobile lending on digital wallets). Correlation coefficient ranges from -1 to +1; where a negative coefficient value signifies negative correlation and vice versa. Moreover, coefficient value above 0.3 was considered strong as indicated.

Regression analysis was carried out to establish which of the independent variables of the study have impact of credit score for mobile lending on digital wallets. It provides the relationship that independent and dependent variables have between them. Generally, regression analysis reveals the degree of changes in credit score as a dependent variable caused by social network data, mobile phone data and transaction data as independent variables of the study at .05 level of significance. Thus, the section first provides the model summary findings, analysis of variance, correlation and regression coefficients as discussed.

Table 4.9 Model Summary Findings

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.419[a]	.271	.246	.4905

a. Predictors: (Constant), Social network data, Mobile phone data, Transaction data

Source: Field Data (2020)

Model summary table 4.9 presents the findings on the extent to which changes in the credit score for mobile lending on digital wallets are caused by changes or variations in independent variable of the study. R represents correlation coefficient which shows the relationship between independent and dependent variables of the study. Therefore, an R of .419 indicates a positive relationship between the variables. R^2 (R square) of the model was estimated at .271 which reveals that 27.1% of changes in credit score for mobile lending on digital wallets is caused by variations in social network data, mobile phone data and transaction data. That means, other changes, 72.9%, are caused by other variables not included in the study objectives.

Table 4.10 Analysis of Variance (ANOVA)

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5.027	3	1.674	6.963	.000[b]
	Residual	63.286	263	.241		
	Total	68.313	266			

a. Dependent Variable: Credit Score
b. Predictors: (Constant), Social network data, mobile phone data, transaction data

Source: Field Data (2020)

Table 4.10 on ANOVA findings established regression model of the study. It was estimated to show how well the model fit the study. Findings indicate that the model was significant at .000% level of significance which is an indication that the data was ideal for making study conclusions as the level of significance was less than .05. F statistics of 6.963 which was obtained as the ration of Mean Square Regression to the Mean Square Residual further showed that the model of the study was significant as indicated by the significance level of .000[b] < .05, revealing that changes in dependent variables are caused by independent variables of the study. As such, this is in accordance to the assumptions made by Saunders, Lewis and Thornhill (2007) that the model of a study is significant if significance level is set at 0.05.

4.6.1 Relationship between Social Network Data and Credit Score

The correlation findings presented in table 4.11 of the study established a negative correlation coefficient value of -.010 between social network data and credit score for mobile lending on digital wallets at significance level of .434 > .05. This implies that the strength of the linear relationship between the two variables is significantly weak and negative. However, the regression analysis results presented in table 4.12 provided a positive regression coefficient value of .158 between social network data and credit score for mobile lending on digital wallets at .070 > .05. This implies that there is a positive relationship between the variables however, the relationship is insignificant, unlike in the previous studies (Niu, Ren, & Li, 2019).

Table 4.11 Correlation Analysis Findings

Correlations

	Pearson Correlation Coefficient Findings				
Study variables		Credit score	Social network data	Mobile phone data	Transaction data
Credit score	Correlation	1			
	Sig. (2-tailed)				
	N	267			
Social network data	Correlation	-.010	1		
	Sig. (2-tailed)	.434			
	N	267	267		
Mobile phone data	Correlation	-.206**	.369**	1	
	Sig. (2-tailed)	.000	.000		
	N	267	267	267	
Transaction data	Correlation	.096	-.148**	.200**	1
	Sig. (2-tailed)	.059	.008	.001	
	N	267	267	267	267

**correlation is significant at the 0.01 level (2-tailed)
**Correlation is significant at the 0.05 level (2-tailed)

Source: Field Data (2020)

4.6.2 Relationship between Mobile Phone Data and Credit Score

Secondly, the correlation results as presented in table 4.11 of the study demonstrates that correlation which is the measure of the strength of the linear relationship of the variables as represented by coefficient value of -.206, was negative at significance value of .000 < .05. This implies that the linear relationship between these two study variables was negative however, significant. Additionally, regression analysis was conducted. The results presented in table 4.12 of the study established a negative regression coefficient value of -.319 between mobile phone data and credit score for mobile lending on digital wallets, at significance level of .000 < .05. This suggest that there is a significant negative relationship between the two variables of the study. The findings disagreed with previous findings (Huang, 2019; Bjorkegren & Grissen, 2015; Shema, 2019)

4.6.3 Relationship between Transaction Data and Credit Score

Lastly under inferential analysis, the study established the correlation and regression between transaction data and credit score for mobile lending on digital wallets. Correlation results presented in table 4.9 indicated a positive correlation coefficient value of .096 and a significance value of .059 > .05. This therefore mean that the strength of the linear relationship between these two variables is positively weak and insignificant. However, the regression analysis results presents a positive regression coefficient value of .219 and a significance value of .007 < .05. This suggest that of the three variables of the study, there is a significant positive relationship between transaction data and credit score for more lending on digital wallets. The findings supports previous findings that transaction data is critical in determining whether borrowers will pay on time (Jayakumar, 2019; Nordigen, 2017).

Table 4.12 Regression Coefficient Findings

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	2.551	.322		7.926	.000
	Social network data	.158	.087	.120	1.819	.070
	Mobile phone data	-.319	.075	-.284	-4.274	.000
	Transaction data	.219	.080	.170	2.730	.007

a. Dependent Variable: Credit Score

Source: Field Data (2020)

4.6.4 Regression Model

As discussed in the methodology of the study, the ordinary linear regression model of the study was explained as follows;

$$\gamma = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon$$

Where γ = credit score for mobile lending on digital wallets

β_0 = Constant

$\beta_1 - \beta_3$ = Coefficient of variables

X_1 = Social Network Data

X_2 = Mobile/phone Data

X_3 = Transaction Data

ε = error term

Thus, based on the regression coefficient values obtained in regression analysis, regression equation was;

$$\boldsymbol{\gamma = 2.551 + 0.158X_1 - 0.319X_2 + 0.219X_3}$$

From the equation output of the study, if all factors are held constant; that is, social network data, mobile phone data and transaction data, consumer credit score for mobile lending on digital wallets would stand at 2.551. However, variations such as introduction in use of alternative data like transaction data and social network data would improve the consumer credit score by .219 and .158 respectively. Thus, the findings clearly demonstrates a positive relationship between transaction data, social network data and credit score. The findings of this study concur with the previous findings of Westerlund (2019) and Nordigen (2017) which indicated that transactions such as bank accounts and payment history add more value for Fintech firms when building credit score for each individual consumer in the market. Also, it agrees with Majumder (2019) who stated that alternative data such as social media data are emerging as inclusive in building credit score for individual consumers in the digital lending market. Mobile phone data relates negatively with credit score. This disagrees with the previous findings by Huang (2019) who argued that how individuals arrange their contacts, write messages and make calls is essential in building their credit score.

CHAPTER FIVE

DISCUSSION, CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

This research described the role of alternative data in accurately determining the credit score for mobile lending on digital wallets in Kenya. The study aims to determine whether consumers have relevant knowledge on how Fintech firms or mobile lending firms use alternative data in building their credit score, and how relevant policies on the use of alternative data can be implemented. The main research objective is broken down into three; to establish the relationship between social network data and credit score for mobile lending on digital wallets; to find out the relationship between mobile phone data and credit score for mobile lending on digital wallets; and lastly, to determine the relationship between transactions data and credit score for mobile lending on digital wallets.

Chapter two of the study provided literature review of the study while chapter four provided presentations of findings of the study. This chapter therefore brings the findings in these two chapters of the study together and positions them in the wider theoretical and policy debate. This chapter is divided into five sections. The first section summarizes the discussion of the findings in line with the findings in the literature review based on research objectives. The second section provides summary of conclusions of the study and contribution to knowledge. The third section provides policy recommendation of the study while the fourth section discusses areas of further research. Final and last section of the chapter summarizes limitations of the study.

5.2 Discussion

This section summarizes the findings of the study in the previous two chapters of the study (chapter two and four) based on the research objectives. First, the study was grounded on the theory of innovation diffusion and financial intermediation. The two theories were relevance in guiding the objectives of the study explicitly. First, the emergence of big data through technological innovation has seen the rise of use of all types of in decision making. Technological firms that provide digital loans therefore relies on this this theory of innovation diffusion to utilize majorly transaction and mobile phone data of their consumers in building their credit score. Additionally, financial market is faced with issues of information asymmetry, which makes small Fintech firms to lack critical information of their consumers mostly from the regulated Credit Bureaus. For this reason, financial intermediation theory was relevant in the study in describing intuitively how Fintech firms can utilize the available information such as social network data in building the credit score for their individual consumers.

The study used exploratory design with two sample group; individuals and micro informal businesses, thus the total sample size of the study was 350 respondents. However, the study was able to obtain a response rate of 76%. Majority of the participants in the study were male with most of them having other levels of education (neither bachelor's, post-graduate nor diploma). While reasons for taking loan remained ambiguous, majority of the respondents indicated that the sector that best describes their business idea are trading and services sectors. Also, they indicated that Tala and Branch are the mostly downloaded mobile lending apps. As for Safaricom mobile apps, they indicated that they automatically find MSHWARI and KCB MPESA services linked to their mobile lines, thus do not have to download MySafaricom App. However, they download it for other services such as MPESA statements on a monthly basis. Therefore, discussion of the study was as follows;

5.2.1 Social Network Data and Credit Score for Mobile Lending on Digital Wallets

This project addressed social network data in line with individual social media accounts. It first aimed to determine the relevant knowledge of consumers on the use of social media as an alternative data and secondly, to find out the relationship between social network data and credit score. The social network accounts included Facebook account, Twitter, LinkedIn account and Instagram. This was based on the existing literature which has argued for the use of social accounts information in determining the credit score for consumers. From the descriptive findings of the study, the study established a composite mean which suggested that level of knowledge on the use of social network by Fintech firms in providing mobile lending services among the consumers is minimal. This was based on participants' level of disagreement that the information on their social media accounts reflected their personality.

Correlation results between social network data and credit score for mobile lending on digital wallets established insignificant negative correlation. Connecting this finding to the participants' views during data collection, it could be due to lack of sufficient policy on effective use of social network account in the public domain, especially among mobile lending consumers. Despite studies such as Chui (2013) and Jenkins (2014) indicating that Fintech firms are relying more on network based on social media data to determine borrowers' creditworthiness, the correlation analysis of the current study differs in the findings. The use of social media accounts however has increased steadily, due to technological advancements and internet use which has also changed the dynamics in the financial sector.

Moreover, the study conducted a regression analysis to establish the relationship between social network data and credit score for mobile lending apps on digital wallets. The analysis aimed to show how changes in the credit score of consumers by mobile lending firms are caused by changes in the social network data. Findings revealed that there is insignificant positive relationship between social network data and credit score for mobile lending on digital wallets. That is, social network data have insignificant impact on credit score of consumers. Using artificial intelligence, mobile lending firms are able to obtain social media information of a borrower, the close connections and also uses the personality of the network to determine the possibility of loan default. This is in agreement with the previous findings of Williams (2016) whose study in China and US stated that mobile lending firms have been experimenting with social media data or profiles in peer-to peer lending services.

5.2.2 Mobile Phone Data and Credit Score for Mobile Lending on Digital Wallets

The second empirical objective of the study was concerned with the relationship between mobile phone data and credit score for mobile lending on digital wallets. This objective was justified by the strong emphasis given on uses of borrower's call logs, nature of messaging, mobile phone subscriptions such as data, calls and messages as well as uses of downloaded phone apps by Fintech firms in building their credit score for mobile lending services. Descriptive findings indicated that among mobile lending consumers, there is disagreement on the relevant use of mobile phone data in building their credit score. Majority of the respondents disagreed that they observe wording and punctuations of their messages, thus a clear indication on lack of policy knowledge on mobile lending firms' uses these information in building their credit score.

The study also established significant weak correlation between mobile phone data and credit score for mobile lending on digital wallets. That is, their levels of disagreements with most measurements of mobile phone data clearly suggest that they do not have effective knowledge that mobile loan providers may secretly be observing their phones, how they use their phones as well as the apps they are having in building their credit score. Despite Huang (2019) indicating that mobile phone data as a type of alternative data is easily available, accessible and replete with the information that mobile lending firms use for credit score as it highlights borrower's lifestyle and economic activities, the finding of the current study disagrees with this notion, as indicated by estimated negative correlation.

The study also carried out a regression analysis to estimate the extent of changes in credit score for mobile lending on digital wallets caused by changes in mobile phone data. The results established a significant inverse relationship between mobile phone data and credit score for mobile lending on digital wallets. While previous studies have argued for the use of mobile phone data by mobile lending providers in determining the creditworthiness and trustworthiness of borrowers in the mobile lending market, this study differs with these views; especially with those of Eilin, Blumenstock and Robinson (2017) who studied digital banking and concluded that due to challenges in accessing credit services by consumers in the emerging market, alternative data such as mobile phone data can be used. Mobile data involved call detail records, application usage and messaging contents.

5.2.3 Transaction Data and Credit Score for Mobile Lending on Digital Wallets

The third and final empirical objective of the study was to determine the relationship between transaction data as an alternative data and credit score for mobile lending on digital wallets. Transaction data involves payment history which can be utility bills, debit or credit account transactions of borrowers, as well as paying other bills such as shopping using MPESA. From the descriptive findings of the study, it was established that most respondents have not understood how mobile lending service providers utilizes an individual borrower's transaction data records in building their credit score. To them, they only receive certain limits of borrowing without effectively understanding how these firms develop these financial borrowing limits.

Of the three variables of the study, the study established that only transaction data had a positive but insignificant correlation with credit score for mobile lending on digital wallets. Financial records have remained a big determinant in developing creditworthiness of consumers both as a traditional and an alternative data. In the age where technologies and internets thrives, Fintech firms use artificial intelligence (AI) to establish borrowers' transactions records both MPESA transactions and bank transactions and uses the information in building their credit score. These findings are in agreement with the previous findings of Nordigen (2017) whose study concluded that transaction data may explain a lot about a borrower's financial stability and the ability to repay borrowed money on time.

Also, the study established a positive relationship between transaction data as an alternative data and credit score for mobile lending on digital wallets in Kenya using regression analysis. This implies that improved transaction records of an individual can improve their credit score as it states the level of financial stability and liquidity of his or her financial position as a borrower. The findings concur with the previous research of Verkade (2018) who carried out a study on the benefits of transaction data on credit score for SMEs and found out that transaction data contains useful information that mobile lending providers use in determining individual consumer's default rate and creditworthiness. It enables Fintech firms to identify more than 50% of their defaults on average and develop effective ways of avoiding such risks in the market.

5.3 Conclusions

This study focused on exploring role of alternative data in accurately determining credit score for mobile lending on digital wallets in Kenya. Foremost among the alternative data identified in the study as predictor variable included social network data, mobile phone data and transaction data which formed the predictor variables of the study. In the age where technology advancement and internet use is defining the financial industry, Fintech firms have been tipped to aid in the goal of financial inclusion. This study therefore sought to not only establish the relationship between these predictor variables and credit score, but also to describe the general knowledge of the participants on the use of alternative data by mobile lending providers in determining their credit score. As discussed in the previous section 5.2 of this chapter, the conclusions of the study were based on findings and discussion of the study according to objectives of the study.

5.3.1 Social Network Data and Credit Score for Mobile Lending on Digital Wallets

High rate of default among borrowers have forced Fintech firms to develop mechanisms of determining who to lend to and the possibility of borrowers repaying on time. The study established that indeed social network data as an alternative data has a positive relationship with credit score. The study therefore concludes that mobile lending providers utilizes borrowers' social media accounts in building their credit score. This is aimed first by determining the network of the borrower and uses artificial intelligence to determine the personality of the borrower based on the information on their social media accounts. As a result, the study further concludes that there is a high possibility that individual with a small network and information that fully reflects their personality have a high rating score than their counterparts who do not understand the significance of social media account information as employed by the Fintech firms when providing peer-to-peer lending.

5.3.2 Mobile Phone Data and Credit Score for Mobile Lending on Digital Wallets

The study concludes that mobile phone data such as call log details and contents of messaging are inversely related to credit score for mobile lending on digital wallets in Kenya. Of the three predictor variables of the study, findings concludes that it was only mobile phone data that had negative or inverse relationship with credit score. Thus, evidence demonstrates that while previous studies indicate that mobile lending providers may look into the call logs of consumers to determine their lifestyles, findings of this study concludes that there is correlation or relationship between the two variables of the study. Hence, changes in mobile phone data results to reduction of credit score capacity of an individual consumers in the market among the mobile lending providers.

5.3.3 Transaction Data and Credit Score for Mobile Lending on Digital Wallets

The study explored the relationship between transaction data and credit score for mobile lending on digital wallets in Kenya. The study concludes that mobile lending firms use transaction data of individual consumers to build their credit score. Transaction data that Fintech firms utilizes when designing credit score include forms of mobile payments such household subscriptions, frequent use of credit cards, how faster borrowers pay their subscriptions on a monthly basis when they fall due as well as other online and offline payments. Consumers who pay their arrears on time and when they fall due may be regarded as trustworthy and creditworthy borrowers who have the ability to repay their debts when they fall due, thus having a high credit score than their counterparts with late payments. The study further concludes individuals with frequent transaction records have a high credit score among mobile lending providers in the market.

5.3.4 Contribution to Knowledge

The primary goal of the researcher in this study is to look at the concept of alternative data and credit score for mobile lending on digital wallets on a new perspective. To date, most studies covering these two key areas have focused on the lenders or digital loan providers themselves or used secondary data.

In this study, the researcher has attempted to shift the focus to the issues related to alternative data from the borrowers' perspectives rather than from the perspectives of lenders or digital loan providers. Moreover, the study uses primary data as an aim to get first-hand information on the participants or borrowers' understanding of how mobile credit digital providers uses their information, specifically, alternative data in building their credit score.

As such, the emergence of online credit borrowing boosted by the global call for financial inclusion is an indication to truly establish the relevance of alternative data, and how these data can be protected to ensure that it is only used for credit purposes. Therefore, this study emphasizes on the need to build a comprehensive data privacy policy framework that is specifically aimed at building the credit score for digital credit services. For some years now, mobile lending on digital wallets has remained a challenge in emerging markets, especially due to lack of adequate online financial regulations. The findings of this study provides mechanisms and relevancy on the need to develop a well-regulated digital financial market policies that protect both borrowers and consumers.

5.4 Policy Implications

The discussion and conclusions of this study have a number of policy implications. First, in comparison to the existing literature, this thesis executes a more systematic exploration of alternative data in accurately determining credit score policy for mobile lending on digital wallets. In addition to accurately describing social network data and mobile phone data as alternative data, this study also examined transaction data which for many years, borrowers have not understood how Fintech firms use them in building their credit score. Therefore, the study aims in guiding policy making where mobile lending firms can design policy frameworks that effectively aim at achieving financial inclusion as currently included in the Millennium Development Goals.

Second, this study suggests that the policy goals formulated by both financial regulators and mobile lending providers should be clearer. The experience from the literature of the study as well as mobile lending services in Kenya suggest that the existing policies does not automatically translate into practice where alternative data effectively employed in developing borrowers' credit score are used effectively. Implementing alternative data policies therefore require the government to involve stakeholders from all sectors as well as consumer representatives, by ensuring that the consumers understand how digital wallet firms utilise these data accurately in determining creditworthiness and default rates of an individual.

5.5 Recommendations

From findings, discussion and conclusions of the study, a number of recommendations have been made in relation to the government and mobile lending providers.

5.5.1 Government

To achieve financial inclusion, government should find effective frameworks of encouraging financial lenders to develop ways that can bring citizens into the financial system by having access to financial services. This study recommend that one way for government to ensure that citizens have access to financial services is through developing laws that guides the use of alternative data by mobile lenders in giving mobile loans to informal sectors or borrowers in the country. Data issues such as privacy have arisen most of the time, thus how Fintech firms in the financial sector utilize data should be closely monitored by the national government and this require policy frameworks.

5.5.2 Mobile Lending Providers (Fintech Firms)

How mobile loan providers determine their credit score continues to differ. Thus having a uniform policy framework will be a challenge across the firms that use technological devices to provide loan apps. However, this study recommends that each firm should develop policies that discourage biasness in giving out loans to consumers. Alternative data use remains underutilised especially among the informal sectors. These companies therefore should find a way of incorporating other alternatives as well as transaction data which has been found to be positively related to credit score of a borrower.

5.6 Recommendations for Future Studies

The current study was carried out on borrowers; both individuals and micro informal businesses as the target respondents for the study. While the information gathered may be important in assisting in streamlining alternative policies in Fintech firms, these respondents may not have fast-hand information regarding how the mobile lending market operates. Due to this limitation, this study recommends that a similar study should be undertaken in the future but with Fintech or mobile lending providers as the target respondents.

5.7 Limitations of the Study

Findings of this study are based on quantitative data gathered from individual and micro informal businesses in parts of Nairobi. Also, the findings of this study may not be generalized to other locations because the sample size was based on purposive sampling rather than representative sampling, and the sample size may not be large enough for some particular issues discussed in the study. However, this limitation of generalization perhaps could be overcome by carrying out further study on a similar topic but with different samples and in different location.

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APPENDICES

Appendix 1: Letter of Introduction

Dear respondent,

My name is Anthony Gathu, a student at Strathmore University Business School in Nairobi, Kenya, undertaking a course in Master of Public Policy and Management. I am undertaking an academic research on "Alternative data and credit score for mobile lending on digital wallets." You are kindly requested to take part in this survey and your participation in this questionnaire is voluntary and will help to achieve the research objectives.

Kindly note that your response will be used for the purpose of this study only and the highest level of confidentiality will apply to any information provided. Your answer will remain anonymous and strictly confidential and in no instance will your name be mentioned in this report.

In case of any questions on the survey, kindly contact me via anthonygathu@gmail.com

The questionnaire will take approximately 10 minutes of your time to fill. Thank You.

Appendix 2: Consent Form

Topic of study: ***An Exploratory Study on The Role of Alternative Data in Accurately Determining the Credit Score for Mobile Lending on Digital Wallets in Nairobi, Kenya.***

Foreword: To Study Participant.

Investigator: Anthony Gathu (Master of Public Policy and Management) Strathmore University.

Contact: Tel. No: +254 722 722 464; Email.

Purpose of the Study: The study aim to explore the role of alternative data in accurately determining the credit score for mobile lending on digital wallets in Nairobi, Kenya. The significance of the study will be to improve policy on data privacy and developing effective credit score for individuals.

How to participate: You will be approached and asked to give information and your opinion on some questions which will be asked in relation to alternative data and credit score. This may take approximately 8-12 minutes of your time.

Voluntary to participate: Participating in this study is a personal choice. Should you decide to participate and later on change your mind or withdraw, your right will be respected and you will be free to withdraw your consent at any time, since there will be no victimization.

Confidentiality and privacy: All the information you give will be treated with utmost confidentiality since the study will be for academic purposes only. Giving information such as names and contact numbers will be optional, and should you decide to give, the information will be protected.

Risks and benefits: There are no risks associated with the study. Also, there will be no any direct benefits to you for taking part in the study.

Should you have further questions, please contact the following;

Investigator: Anthony Gathu (0722722464); Email: anthonygathu@gmail.com

Research supervisor:

Enquiries to: The Secretary-Strathmore University Institutional Ethics Review Board, P.O Box 59857-00200, Nairobi; Emails: ethicsreview@strathmore.edu; Tel No: +254 703 034 375

Your signature implies that the study has been explained to you, and that you have been given the opportunity to ask questions, and that you agree to take part in the study

Signature: ………………………… Date: ………………………………..

For Official Use:

Name: ……………….......... Signature: …………….. Date: ……………….

(Of Research Personnel)

Appendix 3: Ethical Approval Letter

Strathmore
UNIVERSITY

12th March 2020

Mr Gathu, Anthony
anthonygathu@gmail.com

Dear Mr Gathu,

RE: Exploring Alternative Data leading to a Credit Score for Mobile Lending on Digital Wallets: A Case Study of Tala App Model

This is to inform you that the SU-IERC has reviewed and **approved** your above research proposal. Your application approval number is **SU-IERC0644/20.** The approval period is **12th March, 2020 to 11th March, 2021.**

This approval is subject to compliance with the following requirements:

i. Only approved documents including (informed consents, study instruments, MTA) will be used
ii. All changes including (amendments, deviations, and violations) are submitted for review and approval by SU-IERC.
iii. Death and life threatening problems and serious adverse events or unexpected adverse events whether related or unrelated to the study must be reported to SU-IERC within 72 hours of notification
iv. Any changes, anticipated or otherwise that may increase the risks or affected safety or welfare of study participants and others or affect the integrity of the research must be reported to SU-IERC within 72 hours
v. Clearance for export of biological specimens must be obtained from relevant institutions.
vi. Submission of a request for renewal of approval at least 60 days prior to expiry of the approval period. Attach a comprehensive progress report to support the renewal.
vii. Submission of an executive summary report within 90 days upon completion of the study to SU-IERC.

Prior to commencing your study, you will be expected to obtain a research license from National Commission for Science, Technology and Innovation (NACOSTI) https://oris.nacosti.go.ke and also obtain other clearances needed.

Yours sincerely,

for: Dr Virginia Gichuru,
Secretary; SU-IERC

STRATHMORE UNIVERSITY INSTITUTIONAL ETHICS REVIEW COMMITTEE (SU-IERC)
12 MAR 2020
TEL: +254 (0)703 034 000
P. O. Box 59857 - 00200
NAIROBI - KENYA

Cc: Prof Fred Were,
Chairperson; SU-IERC

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Appendix 4: NACOSTI Research Permit

REPUBLIC OF KENYA

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Ref No: 751034

Date of Issue: 27/March/2020

RESEARCH LICENSE

This is to Certify that Mr.. Anthony Gathu Gathu of Strathmore University, has been licensed to conduct research in Nairobi on the topic: EXPLORING ALTERNATIVE DATA LEADING TO A CREDIT SCORE FOR MOBILE LENDING ON DIGITAL WALLETS: A CASE STUDY OF TALA APP MODEL for the period ending : 27/March/2021.

License No: **NACOSTI/P/20/4536**

751034

Applicant Identification Number

Director General
NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Verification QR Code

NOTE: This is a computer generated License. To verify the authenticity of this document, Scan the QR Code using QR scanner application.

Appendix 5: Research Instrument

INTRODUCTION

This survey tool seek to gather information on "**An Exploratory Study on the Role of Alternative Data in Accurately Determining the Credit Score for Mobile Lending on Digital Wallets**." You are therefore requested to participate in the study by providing accurate and reliable information which shall help in shaping the credit score policy frameworks on small businesses and individuals in accessing loan. Your answers are confidential and shall be used for academic purposes only.

SECTION A: DEMOGRAPHICS

First, we have general questions for you

1. Please, indicate your name

   ____

2. Please, provide your phone number

   ____

3. What is your gender?

   Male [ ] Female [ ]

4. Age category

   Below 20 years[ ] 21 – 30 years [ ]

   31 – 40 years [ ] 41 – 50 years [ ]

   51 – 60 years [ ] Above 60 years [ ]

5. Level of formal Education

   Undergraduate [ ] Graduate [ ]

   Post-graduate [ ] Other [ ]

6. What sector best describes your business idea in the SME sector

   Trading [ ] Service [ ]

   Agribusiness [ ] Manufacturing [ ]

   Others (Specify ....)

7. What mobile lending apps do you use?

   Tala [ ] Branch [ ]

   Safaricom app (KCB MPESA, MSHWARI) ____________________

   Others _______________________________

8. Have you been an active mobile loan app user?

   Yes [ ] No [ ]

9. How long do you take to repay a loan?

Within the week	[ ]	Two-Three Weeks	[ ]
Four weeks	[ ]	Above Four Weeks	[ ]

10. If you understand the context of alternative data in credit scoring, how would rate its usefulness in credit score by Fintech firms?

Very High	[ ]	High	[ ]
Moderate	[ ]	Low	[ ]

SECTION B: ALTERNATIVE DATA USE IN CREDIT SCORE FOR MOBILE LENDING WALLETS

SOCIAL NETWORK DATA

11. ***Social Network Data*** *– involves looking at how Fintech firms use social media accounts (Facebook, Twitter, LinkedIn and others) to build credit score.*

The following statements describes usefulness of social network data variable in credit scoring. Kindly indicate your level of agreement with each factor in a scale of 1-5 where 5-strongly agree (SA), 4-agree (A), 3-neutral (N), 2-disagree (D) and 1-strongly disagree (SD).

Statements	**SA**	**A**	**N**	**D**	**SD**
Are the information on your social media accounts genuine ones?					
A part from Facebook, Twitter, and Instagram, which other social media accounts are you registered in?					
Do you spend too much of your time on social media, even at night?					
Do you often communicate to your family using other social media accounts such as WhatsApp?					
Do you rely on your social media accounts to know the breaking news?					
Do you find using social media accounts easier and cheaper than phone calls?					
Do you have an idea that your social media accounts should reflect who you are?					

MOBILE PHONE DATA

12. ***Mobile Phone Data*** *– involves checking the contents of call records, text messages and application usages and how they can be useful in building credit score for borrowers.*

The following statements describes usefulness of mobile phone data usage in credit scoring.

Kindly indicate your level of agreement with each factor in a scale of 1-5 where 5-strongly agree (SA), 4-agree (A), 3-neutral (N), 2-disagree (D) and 1-strongly disagree (SD).

Statements	**SA**	**A**	**N**	**D**	**SD**
Would you agree that you have subscribed to daily mobile data, calls and messages?					
Assuming that you do most of your shopping online from online apps such as Jumia, would you say that you purchase expensive mobile data on a weekly/monthly basis?					
How active are all your mobile apps? And do you use all of them on a daily basis?					
Could you confirm that since the introduction of chat apps such as WhatsApp, you have reduced the number of phone calls a day?					
If you get a chance to make a phone call on a daily basis, can you confirm that you do make calls for longer period?					
As a person, do you prefer writing short messages or long messages in a conversation? Including wording and punctuations?					
Would you say you spend too much on mobile data so as to use mobile apps that uses internet?					

TRANSACTION DATA

13. ***Transaction Data*** *– involves checking online/offline payments, bill payments through mobile phones and credit card use to enhance individual's credit ratings.*

The following statements describes usefulness of transaction data usage in credit scoring. Kindly indicate your level of agreement with each factor in a scale of 1-5 where 5-strongly agree (SA), 4-agree (A), 3-neutral (N), 2-disagree (D) and 1-strongly disagree (SD).

Statements	**SA**	**A**	**N**	**D**	**SD**
In the past, have you find it convenient paying for your utility bills using M-Pesa?					
When you cannot go to the bank, do you prefer making cash withdrawals from your bank account using your mobile phone?					
Do you agree that you have more than two credit/debit cards, which are all connected, to your phone number?					
Do you prefer paying for goods and services using phone at all time or you only use phone when buying goods of high prices?					
Would you state that you always leave a small amount in both your bank account, debit/credit cards and your M-Pesa account?					
Do you always prefer making your household subscription payments on time using your phone?					
How often do you always receive your bank/debit/credit/M-Pesa monthly transactions on your phone?					

CREDIT SCORE FOR MOBILE LENDING WALLETS

14. ***Credit Scoring for Mobile Lending Wallets** – involves checking creditworthiness of borrowers, lower aggregate defaulters, identity of borrowers, ease of credit access and lending sustainability using alternative data.*

The following statements describes how mobile lending firms create credit score for their consumers using alternative data. Kindly indicate your level of agreement with each factor in a scale of 1-5 where 5-strongly agree (SA), 4-agree (A), 3-neutral (N), 2-disagree (D) and 1-strongly disagree (SD).

Statements	**SA**	**A**	**N**	**D**	**SD**
I can confirm that I prefer taking loan on mobile lending apps since they provide me with faster processing of loan application?					
I agree that all the information in all my social network accounts are accurate and resemble my personality?					
Since I started using online lending apps, I have found it easy to take loan in other lending apps which I had not used before?					
I can confirm that mobile lending apps ask me certain questions before giving out loan, giving ideas on how to effectively use the money?					
How often have you defaulted your loan and has it reduced your loan application amount in other mobile loan apps?					
I have found lending apps easy to use and very reliable than asking a friend or a family member to give me a small loan.					

Thank you

Appendix 6: Timeline of Activities

Task	**Period (Month)**					
	March - October 2019	November-December 2019	January 2020	February 2020	March 2020	April 2020
Proposal Writing						
Approval of proposal						
Data collection, analysis and report writing						
Submit research report draft						
Research report revision						
Submission of final research report						

Appendix 7: Project Budget

Item	Cost (Kshs)
Printing	6,000.00
Transport	3,000.00
Stationeries (Laptop)	25,000.00
Research Assistants (2)	12,000.00
Data Analysis	10,000.00
Miscellaneous	10,000.00
Total	**66,000.00**