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Mobile credit apps adoption and continuous use in a growing digital economy

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ABSTRACT

Since the launch of Commercial bank of Africa's M-Shwari in 2012, Kenya's first digital banking product which offers a savings account and access to digital credit, the market for digital credit has expanded rapidly in Kenya. Digital credit is now offered by most commercial banks as well as privately developed loan apps from able lenders. In the first two years, CBA through its M-Shwari product had already dished out over 20 million loans to 2.6 million borrowers while Kenya Commercial Bank's KCB-Mpesa helped them to grow from 200,000 new loans per year to about 4,000,000 (Totolo, 2017). A recent report from FSD Kenya indicates that 29 per cent of mobile phone owners in Kenya have borrowed from M-Shwari and there are over 49 loan apps in the country. Also, according to the report, in Kenya's digital lending market share, M-Shwari is leading followed by KCB M-Pesa at twelve per cent, Equity Eazzy at four per cent, Tala at 1.8 per cent and MCo-op Cash at 1.3 per cent (Mbogo, 2018). This paper aims to examine the determinants of Mobile Credit Apps adoption and continuous use in a growing digital economy, case study Kenya.

The researcher used descriptive survey research design. The target population was smart phone users in Nairobi, its environs and 2 rural areas with a good number of mobile smart phone use. The researcher selected a sample of 600 users from the targeted areas. The researcher used purpose random sampling to select the respondents. Data was collected from the primary source. The collection of primary data was done using a combination of structured survey questionnaires and personal interviews, which were administered to the respondents. The data was edited then cording and tabulation was carried out using SPSS. The data was analyzed using qualitative and quantitative techniques.

The findings revealed that the economic factor has a significant effect on the use of mobile credit in Kenya. The research was done on some 600 individuals in Nairobi County and its environs. Practical implications– The findings offer FinTech providers, financial institutions and the government with a better understanding of what contribution digital credit brings to the improvement of individuals' livelihoods. The research contributes to the application of new mobile technology in the financial sector. The findings also help financial institutions consider mobile technologies when aiming to improve financial access to the unbanked individuals.

Keywords: FinTech, digital credit, mobile technologies, digital economy and digital banking.

1. INTRODUCTION

1.1 The Enigma of digital credit

Cash credit is the ability to borrow money from a designated lender with a set limit of both time and value. Information systems and technology in today's business environment has radically revolutionized the financial sector and in tune has produced digital banking facilities. Digital credit is the ability to lend, borrow and pay money by use of a digital electronic device. A few years ago, the financial sector was so stringent when it came to provision of loaning facilities to the extent that a physical appearance was almost absolutely necessary. The mobile lending space in Kenya has since then grown significantly.

Since the early 2000s, Kenya has been touted as a centre of technological innovation from which novel financial offerings have emerged. Mobile company Safaricom's M-Pesa is a well-known example. It is no surprise, therefore, that technology and unregulated lending have developed together so strongly in Kenya (Owuor, 2019). Almost weekly or monthly a new mobile loan app finds its way into the market and these apps have a healthy stream of customers because they offer a service that is traditionally very difficult to access. This is due to the rigidity of banking institutions that require a ton of paperwork, and the difficulty of accessing Saccos that have their set of strict rules (Abuya, 2019).

The mobile lending industry is largely unregulated but includes major financial players. Digital credit providers ranging from commercial banks to small private entities have developed different models to score and deliver credit to customers. The largest players CBA-Mshwari and KCB Mpesa collaborated with the largest telecommunication provider (Safaricom) to score customers and manage loan disbursements and repayments through the M-Pesa platform (Totolo, 2018). The result of these new developments is highly negotiable; while some have used it to grow and generally help themselves others have diminished into a spiraling financial abyss of liabilities.

These new technologies have brought digital innovations and disruptors who have changed the business context and means of interaction. Financial institutions will be required to understand and take advantage of these new changes to compete. Consequently, users have to adjust well to these new financial models by understanding their personal and business needs in relation to the newfound system that gives them access to easy and quick cash. The digital loan services appear to be bridging the gap for Kenyans who do not have access formal banking, or those with incomes not stable enough to borrow from formal financial institutions. These services have improved access to loans, but there are questions about whether the low-income consumers are being abused in the process (Owuor, 2019).

1.2 Financial Technologies

FinTech applications are a strategic part of modernizing and digitalizing your business processes. They are online services and applications, which combine data, functionality and modern user interface to serve your customers any time and place they desire (Exove, 2019). In Kenya, M-Pesa was launched in 2007. It was among the first mobile money services of its kind around and it benefited many people who would have otherwise remained unbanked. The next logical step was to make loans available. The first mobile loans app was launched and issued in 2012 by Safaricom and Commercial Bank of Africa through M-Pesa (Owuor, 2019). A survey released this year (2019), shows that Kenya's population financial inclusion increased from 27% in 2006 to 83%.
Digital credit is a loaning facility that allows a customer to access loans remotely without any cumbersome paperwork using a mobile app or any other form of application. This loans are instant since loan-eligibility decisions are automated based on a set of rules applied to available data and not on human judgement. Once a request is done, customer profiling is done in quick bits using the client's mobile phone-based data, such as calls and SMS records, mobile money transaction history and even social media data to determine a credit score and loan limit (Totolo, 2017).
Most Kenyan banks have launched their own digital credit solutions since 2016, either by collaborating with Safaricom (KCB-Mpesa), establishing an independent virtual mobile network operator (Equity's Equitel) or developing a standalone smartphone app (Cooperative Bank's M-Coop Cash). The repayment process takes almost the same route. A client can either use Mpesa to access the loan repayment options or the app provided by the service provider. The entire process from beginning to end is done remotely.

2. PROBLEM STATEMENT

The concept of digital credit is a fairly new one. In the past five years, digital loans have transformed the market for credit in Kenya. Electronic devices, identity-linked digital footprints, automated credit scoring, agent networks and credit references have enabled providers to deliver loans quickly and efficiently. For most adults, the possibility of borrowing from their phones has opened the door to private, formal consumer credit for the first time (Totolo, 2017). Yet still, the pricing, marketing and potential misuse of these services combined with the extensive negative reporting of defaulters has raised a growing concern about their design and the adverse impacts they have on borrowers and the financial system as a whole.
Digital credit in Kenya comes in a variety of models, including those that use mobile phone apps, mobile money wallets and payroll lending, as well as through a range of provider types, including banks, mobile network operators and even savings and credit cooperative organizations (SACCOs). Many of these digital lenders are unregulated, lending outside the purview of current regulation (Chege, 2016). There are now more than 40 mobile credit applications in Kenya and the hype about the opportunities these new services could offer is now public knowledge. Many users appreciate the convenience and speed of accessing a loan from their phone can be a safer option than informal moneylenders. But, at the same time, such rapid proliferation raises questions about the various ways customers are actually using the products, consumer protection issues and other risks such loans could raise for borrowers (Kaffenberger, 2016).
The services generally offer small-value, short-term loans. With Mpesa, access to the internet was not a real requirement but with majority of the digital credit application services, one should have a smart phone and access to data connections. Connectivity is a must which brings questions of universal access (the digital divide issue) and device affordability. Majority of Kenyans, especially the youth have borrowed beyond what they require and have found themselves in a never-ending debt circle. Generally, what are the motivating factors behind this continuous, expensive and unregulated borrowing?
It is against the backdrop of the above information that the study is designed; to check the determinants of digital credit applications adoption and continuous use in Kenya. According to the researcher's knowledge, in Kenyan context, there has been very little study done to be significant. There is scarce empirical evidence hence this research will envision filling this research gap.

3. LITERATURE REVIEW

There are several concepts that attempt to explain determining factors of digital credit applications adoption. These theories include amongst others; the M-commerce concept and digital financial inclusion concept. Each of these theories makes an assumption regarding the behavior of other aspects of the sector. These theories are useful in addressing the objective and research problem of the current study.

Mobile commerce is the transfer of money using handheld devices with the most common of this being the use of the mobile phones. It is a fast growing phenomenon, which in some parts of the world like Kenya has witnessed a major revolution (Munyao, 2012). M-Pesa followed by Equity Bank's Equitel are the top two mobile money services by value and volume of transactions. The value of mobile commerce transactions in Kenya has passed the Ksh1 trillion ($10 billion) mark this is despite reduction in the number of mobile commerce transactions to 308 million compared to the previous quarter's 352 million (Business Daily, 2018). This concept was used to gauge how Mpesa has helped achieve good standards in international trade.

Financial inclusion can be defined as digital access to, and the use of, formal financial services by the excluded and underserved population (CGAP, 2018). Currently, innovative digital financial services using mobile phones and similar devices have been launched in at least 80 countries to encourage millions of poor customers to exclusively use digital financial services rather than cash-based transactions (GSMA, 2018).

The process of digital financial inclusion begins with the assumption that the underserved population have some sort of formal bank accounts and need digital access to enable them to carry out basic financial transactions remotely. If the underserved population understand and can be persuaded about the intended benefits of digital financial inclusion, an effective digital financial inclusion program should be suited to meet the needs of the excluded and underserved population and should be delivered responsibly at a cost that is sustainable to providers and affordable to customers.

3.1: Economic factors

Mobile money has transformed the landscape of financial inclusion in developing and emerging market countries, leapfrogging the provision of formal banking services. This column explains how mobile money potentially helps improve several areas of market failure in developing economies, including saving, insurance and the empowerment of women (Muellbauer, 2019). It illustrates these effects and concludes that the system-wide effects of mobile money may be even greater than current studies suggest. Mobile money is available in two-thirds of low-to-middle-income countries.

The digital Economy has gained substantial importance within the global economy as a driver of innovation and competitiveness. As part of the global village, this new ecosystem presents a unique opportunity for economic growth. As digital technologies become the cornerstone of daily activities, Governments, businesses and individuals must adapt to this new reality. Going digital is now the bedrock of our economic growth (Digital Kenya, 2019).

In 2018, mobile technologies and services generated 4.6% of GDP globally. The mobile ecosystem also supported almost 32 million jobs (directly and indirectly) and made a substantial contribution to the funding of the public sector (GSMA, 2019). By 2023, mobile's contribution should reach 4.8% of GDP as countries around the globe increasingly benefit from the improvements in productivity and efficiency brought about by increased take-up of mobile services.

For the average consumers who range from low income individuals to those others from the economically 'vulnerable groups' who don't have regular or conventional flows of income like farmers, access to digital finance is currently the only way to receive financial reprieve. Whereas access to credit from formal financial institutions such as commercial banks, microfinance institutions and savings and credit cooperative societies (Saccos) has improved, the digitally delivered micro-credit has significantly increased access and utilization of credit to a large proportion of borrowers previously excluded from formal financial services in developing economies.

Digitally delivered microcredit is easily and conveniently obtained particularly for the previously financially excluded, however, it is an expensive and relatively short-term form of conventional credit (Wamalwa, Rugiri & Lauler, 2019).

3.2: Technological factors

The mobile technological innovation has improved the asymmetric information constraint faced by conventional banks in lending to the low and poor income earners. Also, the movement of cash into electronic accounts for the unbanked and the real-time history of their financial transactions is another factor. Using algorithms, these records provide evolving individual credit-scores that eventually allow users to obtain a pathway to formal financial services accessed only through a mobile phone, e.g. to interest-bearing savings accounts, small loans and insurance products (Muellbauer, 2019). Hire purchase credit is possible through mobile money, permitting secure, remote purchases of costly durable items on a pay-as-you-use basis.

Mobile phone technology has the advantage that users invest in the handset, while a scalable infrastructure is already present for widespread distribution of credit through a secure network channel. By adopting mobile money, under-served citizens gain a secure means of private storage of and transfer of funds and payment safely and at a lower cost.

The Kenyan government through the relevant authorities, granted MVNO (mobile virtual network operator) licenses to several new service providers to enable them offer mobile financial services without building a new cellular infrastructure (Mulwa and Mazer, 2014). Leveraging technologies supports financial inclusion as an effective solution for poverty reduction in developing and poverty-stricken countries. Insights from this study can provide national and global policy makers with an understanding of the issues associated with the rapid development of digital financial services, its delivery to the poor and the risks involved.

3.3 Social factors

The social underpinning factors affecting the use of mobile technology to borrow money are more complicated than they sound. From the fact that we are pushed to multiple borrowing habits by pressures of society to different perceptions from the environment of the knowledge that we have a credit facility. There is little doubt that as consumers our lives have been forever altered by our smartphones, social networking sites, ability to shop online and access to information as we need it, but what does access to mobile loans really mean to our social standing?

A survey conducted by FSD Kenya (Financial Sector Deepening) confirms previous studies that show digital

credit appeals to younger customers who tend to be male (about 55 percent), from urban areas and relatively well educated. However, the customer base for digital credit seems to be diversifying, especially from a gender perspective. Earlier on, this was estimated at a 59 – 41 percent ratio of men to women unique borrowers in digital credit. This survey reduces the gap to a 55 – 45 percent ratio (Totolo, 2018). However, the positive trend in unique borrowers does not mean that the gap is reducing also in terms of volumes and values of digital lending. Interviews with providers confirm that men tend to borrow more often and larger sums on average.
Digital credit has expanded rapidly in both Kenya and Tanzania, yet there is little evidence on who is using it, how it is used and the risks customers face (Kaffenberger, Totolo and Soursourian, 2018).

Some gender differences may emerge in user cases. In Tanzania, women are more likely to report using loans for business purposes, medical needs, and school fees, while men are more likely to borrow to offset domestic obligations or to pay existing loans.
Discussions with digital lenders suggest that a segment of active users who borrow every month or even every week drives growth in the digital credit market. This segment would benefit from opportunities to graduate to larger, more affordable loans with longer repayment periods that can be put to more productive purposes than the current offerings.

Conceptual Framework

In this study, we propose the following hypothesis:
H1: Economic dimension (ED) has a positive effect on digital credit apps adoption and continuous use
H2: Technological dimension (TD) has a positive effect on digital credit apps adoption and continuous use
H3: Social dimension (SD) has a positive effect on digital credit apps adoption and continuous use

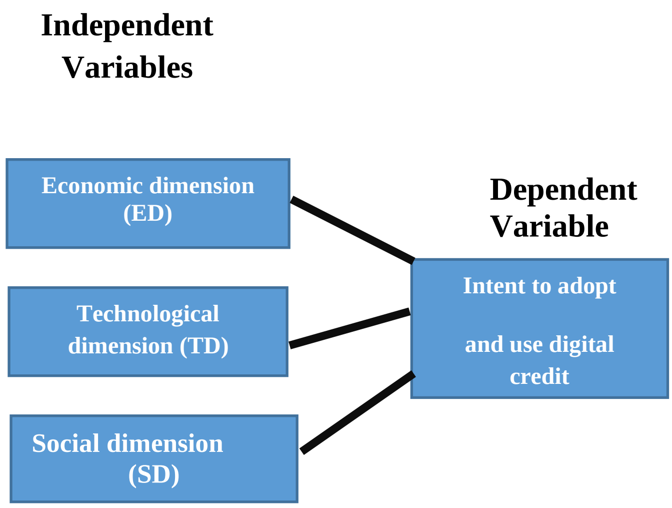

Figure 1: Conceptual Framework

4. METHODOLOGY

According to Burke, a research design is the arrangement of circumstances for collection and analysis of data in a way that aims to combine both relevance to the research purpose and economy in procedure (Burke, 2007). In addition to the fact that this research philosophy is positivist, the relevance, purpose and economy of the methodology adopted was descriptive research design. This design used a cross-sectional approach taking on a survey method that used a questionnaire for data collection.

The target population consisted of smart phone users within Nairobi and its environs. For diversification, the researcher selected two semi-urban areas within Kenya. The researcher selected a sample of participants from each selected zone. According to (Mugenda & Mugenda, 2003) a sample size should be economical and representative. In this case, the total sample size was 600 respondents. Geographical viability and accessibility was the main reason for the chosen sites. Data was collected from the primary source. The collection of primary data was done using interviews and structured questionnaires, which were administered to the respondents. Wherever possible, items used for the development of constructs were adapted from preceding research in order to ensure the content validity of the scale to be used was attained (Gefen, Straub & Boudreau, 2000).

There are no statistical tests to measure validity. All assessments of validity were subject to opinions based on the judgment of the researcher. Nevertheless, there were at least two types of validity that were addressed to assess, these were the face validity and the content validity. These two perspectives were undertaken in the study process. Factor analysis was used to measure if constructs had satisfactory validity and reliability.

5. RESULTS

5.1 Demographics

The sampling frame comprised 600 users from seven towns in Kenya namely Nairobi CBD, Meru, Narok, Machakos, Kiambu, Westlands and Eastlands, The response rate was 70%, which was equal to 420 complete questionnaires. The demographics comprised of 55.7% male and 44.3% female. The age distribution was as follows; 30-39 years represented by 38.6%, followed by those who were between the age bracket of 24-29 years who formed 24.3% of the respondents then followed by the age bracket of 40-50 years who comprised 20.0%. 17.1% of the respondents were above 50 years.

5.2 Research Procedures

There were at least two types of validity that were addressed to assess, these were the face validity, which looked at the likelihood that a question will be misunderstood or misinterpreted. Pre-testing of survey instruments was a good way to increase the likelihood of face validity and Content validity, which looked at whether the instruments to be used will provide adequate coverage in checking the determinants of digital credit applications adoption and continuous use in Kenya. It also did this by use of expert opinions, literature searches and pretest of open-ended questions.

5.3 Correlation analysis

The Pearson's coefficient was used to verify the existence or non-existence of linear correlation between and among the quantitative variables as indicated above. There was some evidence of multicollinearity among the explanatory variables since the correlations among them are strong enough hence, all the variables can be incorporated into the subsequent regression analysis.

Using the information in table 1, it was noted that not all X variables that correlate significantly with Y. Y has a significant correlation with X1, does not correlate significantly with X2 but correlates slightly with X3. In addition, X1 does not correlate significantly with either X2 or X3 but correlates with Y. This can be interpreted to mean that, digital credit applications adoption and use could be predicted individually with measures of economic factors. The measures of technology and social factors were slightly correlated with one another and measures of economics and technology were also not highly correlated. The determinants of digital credit applications adoptions and use could be accurately predicted X1 and X3 but not so by X2.

5.4 Regression Model

R is the multiple correlation coefficient. This means that it's the correlation coefficient between the observed values of Y and the predicted values of Y hence its value will always be positive and will be between 0 and 1. The nearer the value of R is to 1 the greater the correlation between the independent and dependent variables. In this case, the value for the multiple R when predicting Y from X1, X2 and X3 is 69.3%, a high value indicating a high degree correlation between the dependent and independent variables.

R^2 is called the coefficient of determination. It indicates how much of the total variation in the dependent variable, Y, can be explained by the independent variables, X1, X2 and X3. In this case, 48.0% of the variance in the measure of digital credit applications adoption and use can be predicted by measures of economic, social and technology. This is not a high figure but an average degree of correlation.

Further, Table 3, ANOVA, The ANOVA table shows that the model can predict digital credit applications adoption and use using predictor variables. The Sig. column is .000b. This shows that the statistical significance of the regression model that was run, which is less than 0.05, significantly predicts the outcome variable. The model is a good fit for the data.

The sum of Squares for the residual, 14.586 is the sum of the squared residuals. The mean square residual, 0.221, is the squared standard error of estimate. The total sum of squares, 28.063, is the sum of the squared differences between the observed values of Y and the mean of Y.

Finally, the most important table is the coefficients shown in Table 4. Because the significance levels are less than alpha, taken to be .05, then the model was a good fit.

6. DEDUCTION

Experts believe that by 2021, the digital credit market would have grown to double the current subscribers. Digital credit has been instrumental in granting formal credit in ways that were not conceivable a decade ago. It has provided individuals with the tools to manage their day-to-day needs and working capital for small enterprises (fsd Kenya, 2019). Survey data reveals that over six million Kenyans have borrowed at least one digital loan. This study has confirmed this phenomena from its results. From the results of Table 4, The coefficients table above present the optimal weights of the regression model. The difference between non-standardized and standardized regression is that standardized regression does not have a constant. This means that for each item of data, the mean is subtracted and the result divided by the standard deviation.

All values of X and Y under the beta column of the standardized coefficients have been set to a mean of zero and standard deviation of one. In this case, the value of β^0 is zero and is excluded from the equation. The Coefficients table gives us the necessary information to predict the determinants of digital credit applications adoption and use from economic, social and technological factors as well as determine whether X1, X2 and X3 contribute significantly to the model. Because the significance levels are less than alpha, taken to be .05, then the model was a good fit significantly predicting determinants of digital credit applications adoption and use from economic, social and technological factors.

7. CONLUSION

Based on the study findings, digital credit applications adoption and continuous use is eminent. The study concludes that economic factors are very influential in determining the adoption and continuous use of digital credit applications. This shows that most respondents borrow mobile loans to better their economic conditions.

From the study, the researcher recommends that the Kenya government and the finance sector should compile and put in place a formidable digital credit and mobile money policy to act as a guide. Then, financial institutions should be quick to adopt the digital or mobile credit technologies as this will contribute largely in technological advancement and outreach, enhance operational efficiency in terms of credit disbursement and drastically improve the economic status for majority of the citizens. This means that it will help reduce the bureaucratic processes happening in many financial institutions that go a long way in managing to deny people these credit facilities. This technology is in its most basic form, an easier way of reaching and monitoring a majority of the individuals who lack financial inclusion including access to the most basic financial services. The researcher further recommends that people should be made aware of some of the security concerns and risks that come with the use of these new financial technologies. This will help make sure that people are alert and will be able to respond to any arising issues. Finally, it is recommended that banks and other fin tech firms strive to make this service as affordable as possible.

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Table 1: Pearson Correlation

	Y	X_1	X_2	X_3
(Y) Digital Credit Adoption and Use	1.000	.585	-.144	.452
(X_1) Economics factor		1.000	.007	.368
(X_2) Social factor			1.000	.373
(X_3) Technological factor				1.000

Table 2: Regression Model

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.693a	.480	.457	.47011	.480	20.327	3	66	.000

Table 3: ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	13.477	3	4.492	20.327	.000b
	Residual	14.586	66	.221		
	Total	28.063	69			

a. Dependent Variable: Digital credit adoption and use
b. Predictors: (Constant), Economics, social and technological

Table 4: Coefficients

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	1.223	.520		2.354	.022
Economic	.362	.080	.439	4.550	.000
Social	-.207	.068	-.296	-3.059	.003
Technology	.580	.151	.401	3.850	**.000**

Dependent Variable: Digital credit adoption and use