EVALUATING THE IMPACT OF FINTECH PAYMENT SOLUTIONS OF THE GROSS DOMESTIC PRODUCT (GDP) OF EMERGING COUNTRIES WITHIN SUB-SAHARAN AFRICA

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EVALUATING THE IMPACT OF FINTECH PAYMENT SOLUTIONS OF THE GROSS DOMESTIC PRODUCT (GDP) OF EMERGING COUNTRIES WITHIN SUB-SAHARAN AFRICA

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Abstract

Fintech is known to be a pathway with a possibility of increasing economic development, particularly from a financial inclusion perspective. from this research, it has been proven that economical growth or inclusive fintech starts with access and usage of payment services as it lays a foundation for other financial services. This consequently implies that economies struggling with high financial inclusion need to make a paradigm shift towards embracing more fintech solutions. Hence, the focus of this research is mainly centered on evaluating the impact of fintech payment solutions on the Gross Domestic Product of emerging markets in Sub-Saharan Africa. This subject is considered essential because very limited existing works of literature have analytically examined the impact of the fintech payment solution and how it contributes to the growth in an economy. This research also attempts to guide relevant stakeholders to be aware of the most promising subsections of fintech payment solutions. Using regression analysis four models were built with SVR, LASSO, PLSR, and PCR. The rationale behind these models was informed based on their unique ability to address the multicollinearity of highly collated variables without compromising bias or inducing too much complexity. The findings obtained from the models built proved that digital and debit card payments have a significant impact on economic growth and should be areas of interest to these relevant stakeholders seeking to grow the emerging markets in Sub-Saharan Africa. Amongst all the models, the PLSR model was the most accurate with an R^2 value of 97%. This is followed by the PCR model which has an accuracy of 93%. These values go on to conclude that the independent variables – fintech payment solution in this significantly impacts the GDP of the selected countries examined. The results obtained from this research are very optimistic regarding its relevance and how it poses as a start-off point for countries seeking to re-evaluate their approach to solving economic growth and development.

1 Introduction

1.1 Background of Study

The idea of using technology for financial services (FS) goes as far back as the 1950s when credit cards were first created to ease the carrying of cash (Khiewngamdee and Yan, 2019). This technological innovation formed the bedrock for other FS because today, technology is the core of most solutions. Hence, it is almost impossible not to notice that in Gimpel, Rau, Roglinger's work., (2018) these changes imply that the financial sector is experiencing a radical transformation. This transformation led to the creation of '*Fintech'* which is a marriage between '*finance'* and '*technology'*.

Since its inception, there has been no consensus on the definition of fintech. However, with all the academic attempts made to define this term, this research will adopt Schueffel's, (2016) scientific approach to defining fintech. From Schueffel's research, '*fintech is a new financial industry that applies technology to improve financial activities'*. The general idea in fintech lies in using its solutions to challenge the status quo amongst traditional FS providers like banks. Today, fintech is popularly known for enhancing services or introducing new technological innovations that can affect day-to-day living. They include mobile banking, blockchain, cloud computing, and big data. In Khiewngamdee and Yan, (2019), fintech's approach to solving man's common challenges is also evident in solutions built to improve man's financial payments experience. Consequently, the priority of this research is streamlined to fintech payment solutions, one of the fastest rising areas of fintech. Almost daily, it is recorded that another fintech payment start-up has been added to the growing statistics within emerging markets (EM). This is expected because of the low penetration rate and the demanding requirements needed by banks to carry out services like Know-Your-Customer (KYC). These challenges thereby make the use of fintech solutions a necessity rather than a fancy industry. A large part of FS revolves around individuals making payments for either a service received, or a product bought. With respect to EM, its dynamic nature within Sub-Saharan Africa (SSA) has made the payments landscape a very lucrative one. Hence, understudying how this sector affects the standard of living of these countries is a conversation that must be had.

World Bank's, (2020) research outlined that payment solutions from a fintech perspective if well leveraged can create more opportunities and improve the access and usage of transactional payments. Payment solutions according to Amromin and Chakravorti, (2007) are '*an overall payment system in countries are a set of payment instruments, banking procedures, and interbank funds transfer systems that enable money to circulate.'* Research by Yao, (2019), argued that the overall increase in the adoption rate of these payment solutions within EM in SSA will go a long way in increasing the demographics and statistics for inclusive fintech. The evolution of payments in FS alongside fintech as outlined in Jun and Yeo, (2016) has been a transition from using bank alternatives and settlement systems to using technologies such as blockchain, non-bank payments networks, digital/mobile wallets, and virtual cards.

In Jun and Yeo, (2016), payment processes are characterized by a combination of diverse activities and stages. Putting into consideration the different stages, payment chain, and the type of services offered, financial and non-financial payment service providers can be said to be divided into four categories with each category having a different focus area. These four categories include front-end providers, back-end providers, operators of retail payment infrastructure and end -to end payment providers. The focus of this research is the end-to-end service providers which include digital payment, credit, and debit cards, etc as these sets of providers interact directly with the consumers.

1.2 Motivation of Study

Over the last couple of years, the payment sector has skyrocketed in terms of investment An Accenture report records that global funding for this arm of fintech rose from $8 billion in 2017 to $12 billion in 2018[1]. This goes on to show that the sector is generally an area of interest to stakeholders.

Therefore, the major motivation for this research is to highlight the impact this arm of Fintech has on the economy to help stakeholders gain clarity on other determinants to the GDP in any economy. An immediate application of this research is to inform policymakers and to add to the growing body of literature regarding measuring the impact of relevant arms of Fintech.

[1] https://www.forbes.com/sites/jeffkauflin/2019/02/04/top-payment-fintech-companies/#6571f9c376c9

1.3 Problem Statement

Low financial inclusion (FI) has been said to be a contributor to the high poverty rate in EM within SSA. To make a transition from this low FI, stakeholders must realize that FI starts with being able to make payments for goods bought and services offered. The World Bank's, (2020) research regarding payments has established that payment solutions remain the gateway to other forms of FS like saving, lending, etc. Benefiting from these forms of FS through fintech's solutions, EMs can gain a financial identity (Maino and IMF, 2019). Weichert, (2017) argues that fintechs with its unconventional business model are realigning payment solutions and how it can meet customers' needs. Although the adoption rate of these solutions is theoretically on the rise, there is still limited analytical evidence to support this claim.

The gap lies herein that there is currently limited literature regarding how fintech payment solutions impact the development of an economy in terms of its GDP. The problem this research is focused on is, evaluating the impact of fintech payment solutions on the GDP per capita of EM in SSA.

1.4 Aim & Objectives of the Study

Having outlined the gap, this research aims to add to the growing body of literature that is evaluating how fintech payment solutions are contributing to the development of EM in SSA. That is, determining if these solutions can be counted as a factor that adds to the growth level of the countries examined. The objectives of this research are:

- Contributing to existing research surrounding fast-growing areas in fintech, but more specifically going beyond carrying out a theoretical study but performing analytical research that will highlight the areas of fintech payment that are impacting GDP in countries in SSA.
- To help investors and entrepreneurs trying to add to the growth of these EM examine if the fintech payment sector is a good value for their resources. Hence, this research intends to be a guide to any fintech stakeholder who seeks to make a guided decision when channeling their resources.

1.5 Research Question

Based on the objectives, the question this research answers is:

Do fintech payment solutions have any impact on the GDP per capita of emerging economies within Sub-Saharan Africa?

1.6 Research Hypothesis

H^0: Fintech payment solutions in EM within SSA do not affect GDP per capita.

H^1: Fintech payment solutions in EM within SSA affect GDP per capita.

2 LITERATURE REVIEW

2.1 The State of Fintech Payment Solution & GDP

Cash remains the predominant method of payment in Africa because several reasons limit the opportunities that formal methods of payments come with (Bech et al., 2018). Statistically, approximately 60% of people within SSA lack exposure or do not use these formal payment methods (Soutter et al., 2019). However, currently, there has been significant growth in the emergence of fintech operations in SSA. These operations as recorded in Soutter et al., (2019) amount to a total of over 260 companies of which the payment service segment enables fintech to obtain more full dominance and faster emergence. The effective use of these payment services which inadvertently helped the overall financial system of countries in SSA was pioneered by the advent of pan-African banks (different from the traditional bank) (Maino and IMF, 2019). A cross-section of the various types of technologies in these payment services includes mobile money, electronic money, peer-to-peer payments, digital currency, and blockchain. Despite these plethoras of technologies supporting payment, mobile money is said to have been the most impactful particularly in the SSA region (Maino and IMF, 2019). This claim is supported in Kang, (2018) research where it was highlighted that most part SSA will begin to adopt mobile payments, and this growth of embracing fintech payment solutions (FPS) will continue to increase tremendously till 2006.

From a developmental perspective, there is a correlation between increasing FPS and FI which is related to a country's GDP. Rahmi, (2019) postulated that in Indonesia, an increase in FI through relevant fintech sectors can boost the economy's GDP per capita by 0.03%. This growth if traced back to FPS can further encourage exponential growth that can lead to creating more job opportunities for its citizens. In the case of Nigeria, Ajiboye et al., (2013) literature gave a macroeconomic overview where Nigeria recorded a real GDP growth rate of 6.5% in 2012. At this time, the country was dominated mostly by the use of ATM of transactional payments and also had over 48.4 million internet users. On a global scale, countries that recorded a growth in the use of FPS noticed an increase in their economical growth at roughly the same percentage. For example, the impact of card usage in the US-led to a rise in its GDP by 0.04%. This same growth is seen in Ireland, Poland, and Greece. Interestingly, there was also a decline in economic growth when a shortage in the usage of card payment solutions was noticed (Zandi et al., 2013).

Finally, various literature has highlighted the possibility of economical growth of different countries as the adoption rate of FPS increases. All things being equal it is expected that this same equation is noticed with SSA but the literature regarding this conversation is very limited.

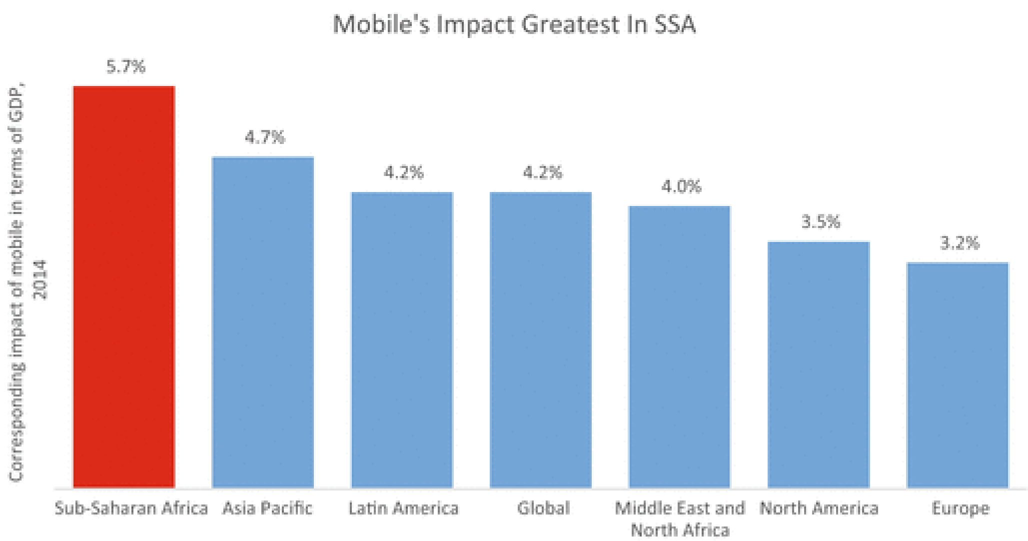


Figure 1: Mobile phone impact by regions | Source: (Osiakwan, 2017)

2.2 The Fintech Payment Considered

2.2.1 Mobile Payments

60% of the adult population in SSA have predominantly been said to be financially excluded either because they have little or no knowledge of traditional means of FS or they have no access to them (Soutter et al., 2019). Recently, these excluded people within Africa have begun to experience a paradigm shift making them more receptive to innovative technologies that can enhance their personal payment experiences. The occurrence of this shift helps to also ensure that these countries gradually prepare for future de-cashing solutions one of which is mobile payments (Alhassan and Koaudio, 2019). Demirguc-Kunt, Klapper, Singer, Ansar, Hess., (2018) confirmed that mobile money a core aspect of mobile payments today has been seen to have rapidly increased in terms of usage across countries within SSA. In SSA it was recorded that mobile money uses grew from 75 million users in 2012 to 340million users in 2017 (Soutter et al., 2019). This growth can be traced back to the M-Pesa solution in Kenya and a few other mobile money solutions that have taken over the internet.

Essentially, Iwasaki, (2017) highlights that the unique selling point for mobile payments in SSA is that these forms of services can be used by people with the faintest exposure to prior technological knowledge when financial services are being discussed. For this reason, the high adoption rate of this solution is considerably comprehendible as it has been established that high barriers to FS are a major cause of exclusion in SSA. In terms of economic development within these countries, Alhassan and Koaudio's, (2019) experiment confirmed that a full transition to adopting mobile money transfer can significantly help the adoption rate of other innovative forms of FPS, triggering a strengthening of the financial infrastructures within these countries and by virtue of the existing relationship between a strengthened financial system and GDP, a country can be said to be prosperous (Ibid).

Fig 2 below shows EM in SSA and the amount of individual with mobile money account. The focus in this image is the ‘mobile money accounts(millions)’ column where the different countries and the amount of mobile money account have been enlisted.

	Characteristic				
Country	Enabling	Dominant Telecom	Moderate / High Population Density	Moderate Economic Freedom	Mobile Money Accounts (millions)
Nigeria	No	Yes	Yes	Yes	< 0.9 (0.5%)
Botswana	No	Yes	Yes	No	< 0.3 (12%)
South Africa	No	Yes	Yes	Yes	< 0.5 (0.01%)
Ghana	No	Yes	Yes	Yes	< 2.0 (7%)
Kenya	Yes	Yes	Yes	Yes	30.00 (80%)
Uganda	Yes	No	Yes	Yes	18.50 (60%)
Tanzania	Yes	No	No	Yes	41.40 (80%)
Zimbabwe	Yes	No	No	No	7.35 (66%)
Somalia	Yes	No	No	No	7.25 (66%)

Figure 2: Mobile Money accounts in Africa (2007 to 2017) | Source: (Soutter et al., 2019)

2.2.2 Credits & Debit Card Payments

Cards payments have been in existence since the last decade but recently, fintechs are recycling the forms in which card payment solutions come. The subject of issuing physical credit or debit cards from banks has raised concerns because of the high rate of cybercrime. As an industry with a focus on tackling daily financial challenges virtual debit and credit cards are now encouraged mainly for the high-level security they come with. According to the World Bank, in SSA it is commonplace to see individuals without access card payments. This is because cash is predominantly king within these SSA. KPMG postulates that if this remains the case then the growth curve for fintech payment will record no change and the use of card transaction may only be as low as 1.7% to be recorded in 2023 (McCurdy et al., 2018). The rationale behind these virtual cards is to reduce the online fraud that occurs when entering card details over the internet (Mumm and Kuppuswamy, 2009). On a broader scale, in Africa, these forms of payment are the most prominent most particularly debit cards, and this has crippled the growth of other forms of payment in terms of usage. But SSA is a different case as it records more use of mobile payment as its preferred form of payment (Yermack, 2018). A finding from (Tchouassi, 2012) literature also highlighted that the use of debit cards in SSA records only about 14 percent progress and adoption of this form of payment is most common amongst the high-income earners withIN a particular country.

2.3.3 Digital Payments

Enabling digital payments and digital FS in any economy helps her stand a chance of being a beneficiary to immense economical impacts like the employment of citizens and productivity as a whole. This digital economy when driven by mostly fintech startups can steer a pathway for societal challenges especially financial inclusion which is a core driver of economic growth in any country (Naboulsi and Neubert, 2018). One of the impacts of such digital is seen in Kenya with the M-Pesa digital/mobile payment solution. In Kendall, Robert, and Emmanuel's., (2013) report, Kenya reported that many startups are embracing and incorporating M-Pesa (a digital/ mobile money fintech payment solution) as a part of their entrepreneurial business model. This impact stems from the adoption of digital payments and usually is also extended to the government as its ripple advantages can be seen in the reduction of payment costs and increased transparency in economical activities such as tax revenues (Yao, 2019). In essence, digital payment solutions offered by fintech startups comes with significant benefits as well as risks. In Yao's, (2019) literature, the benefits of digital payments to EM spoken about usually come in different folds – 1. provision of more accessible methods of money transfer at ridiculously low cost, 2. Enabling the unbanked access to financial services like savings and credits 3. Generation of valuable data that can be used for credit profiling.

Digital currencies, a subsection of digital payments is also one of the fastest-growing FPS. Digital currencies are very similar to paper currencies but they are digital payments that are universally accepted as a legal tender for either public or private transactions (Bordo and Levin, 2017). Although its benefits are extended to some of those listed above, they still pose a considerable amount of risks like fraud, tax evasion, money laundering, and other financial crimes. This is not to say that they must be completely avoided but rather, any Fintech startup offering such financial services needs to double up in terms of security and adhering to financial regulations.

3 METHODOLOGY

This chapter elaborates on the methodology used including the methods adopted, the data selection process, and justification. This chapter gives a general overview of what was done and how the analysis was carried out.

The quantitative data analysis carried out in this research followed the KDD methodology. Inspired by Amromin and Chakravorti, (2007); Khiewngamdee and Yan, (2019) regression models were used to achieve the aim of this research. Fig 3 below outlines this approach and is followed by a further explanation of how it was uniquely approached.

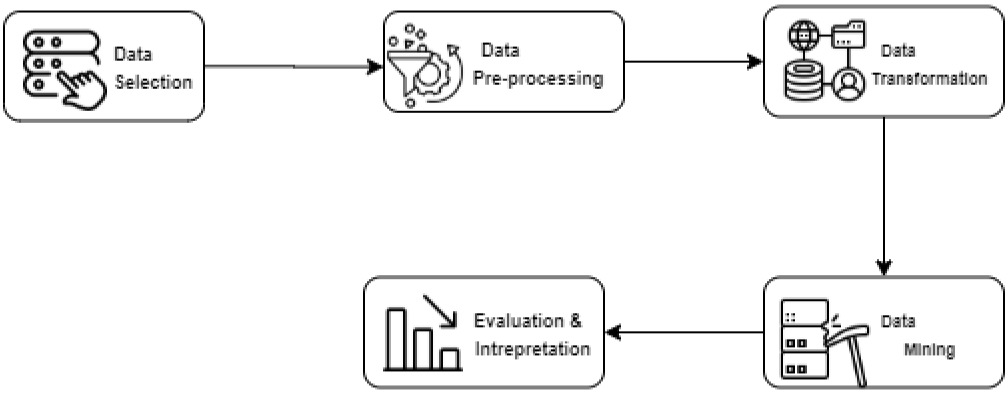


Figure 3: KDD Methodology

3.1 Data Selection & Collection

The data collection phase for this research was primarily done quantitatively using open-source datasets on the web. Two data sources were used and the rationale behind choosing and integrating multiple data sources besides the aim of the study was driven mainly by Lazar et al., (2017). Lazar and his colleagues' highlight that there unending benefits that come with the combination of data sources one of which is a high increase in the quality of the data and an ability to view from different perspectives. These data sources include the following:

- **Global Findex Dataset[2]**: a detailed collection of data containing individual access and usage of financial services and fintech solutions. This dataset contained a record of elaborate payment services offered by Fintech solutions. Although the core focus of the data collected is for measuring financial inclusion it was observed that its variables are closely related to the hypothesis defined and the objective this study aims to fulfill.
- **The Maddison Project[3]:** A single file containing the GDP per capita of over --- countries throughout 1760 - 2016. This data source served as the GDP index used to test the stated hypothesis.

3.2 Method of Analysis

Two analytical tools were used for the analysis. Excel and R programming. Since multiple data sources were used, most of the data cleaning and wrangling to put the data in an adaptable form was done on Excel before importation into R Studio.

From Fig 3 above, it was highlighted that the data were preprocessed. This step was a combination of merging the data sources, changing the different types of the variable, evaluating for duplicates, and checking for missing values. Further analytical steps were carried out during the transformation as a result of the observations that were made during the pre-processing step.

3.3 Evaluation & Justification of Methodological Choices

Prior research within this area of study when carried out used different regression methods to evaluate impact amongst single or multiple independent variables (Cabeza-García et al., 2019). However, because these researches came from a FI perspective adopting basic regression methods like ordinary least square regression was sufficient. This study aims to focus on a particular sector of fintech and this goal required selecting only variables that were

[2] https://globalfindex.worldbank.org/
[3] https://www.rug.nl/ggdc/historicaldevelopment/maddison/releases/maddison-project-database-2018

within this sector. Consequently, to gauge the correlation amongst the independent and dependent variables without letting the impending relationship between the independent variables affect the model, regression models with a capacity to handle correlation amongst independent variables were used to build the model. The rationale behind the use of this methodology largely lies in the hypothesis and the objective as it seeks to clarify the relationship between different FPS and GDP.

3.3.1 Partial Least Squares Regression – PLSR

Multicollinearity once detected in a dataset even in its least form can lead to bias in regression models. To tackle this, Herman Wold, developed the PLSR technique as a multivariate technique for dimension reduction with a purpose to eliminate multicollinearity in a set of independent variables (Mateos-Aparicio, 2011). Mateos-Aparicio goes further to elaborate that building a regression model with PLS produces the most optimal result because its algorithm is built such that it uses the least amount of dimension when predicting the value of the dependent variable Y from X. From a statistical point of view, when trying to evaluate impact in an analysis, according to Wold, Sjöström, Eriksson ., (2001) it is essential to adopt method with a capacity to analyze noisy data while still being able to simultaneously build an unbiased model.

3.3.2 Principal Component Regression - PCR

PCR a statistical technique that has the best of Principal Component Analysis and ordinary least square method (OLS) and combines into one technique. Like PLSR, PCR is commonly used in cases where there is a need to build an effective model but multicollinearity exists. Its algorithm was developed to build models with several exploratory variables. Although this feature is seen as one of its advantages yet it also adds to some of its major flaws. In a bid to choosing specific principal components for the model, *'it imposes constraints on the coefficients of the explanatory variables that have nothing whatsoever to do with how these variables affect the response variable'* (Artigue and Smith, 2019)'. However, this study opted for this methodology irrespective of its flaw because it has a proven record of building accurate models when the correlation of explanatory variables are concerned.

3.3.3 Support Vector Regression – SVR

SVR, a variation of SVM was built to handle regression problems where a non-linear model is to be built. SVR is designed and most efficient in an analysis where a real value function estimation is required (Gunn, 1998). This technique as a supervised machine learning method uses symmetrical loss function and a kernel approach to address the issue of dimensionality reduction amongst variables. This feature is one of the advantages of SVR as its computational complexity and the ability to build a good regression model does not depend on dimensionality reduction (Awad and Khanna, 2015).

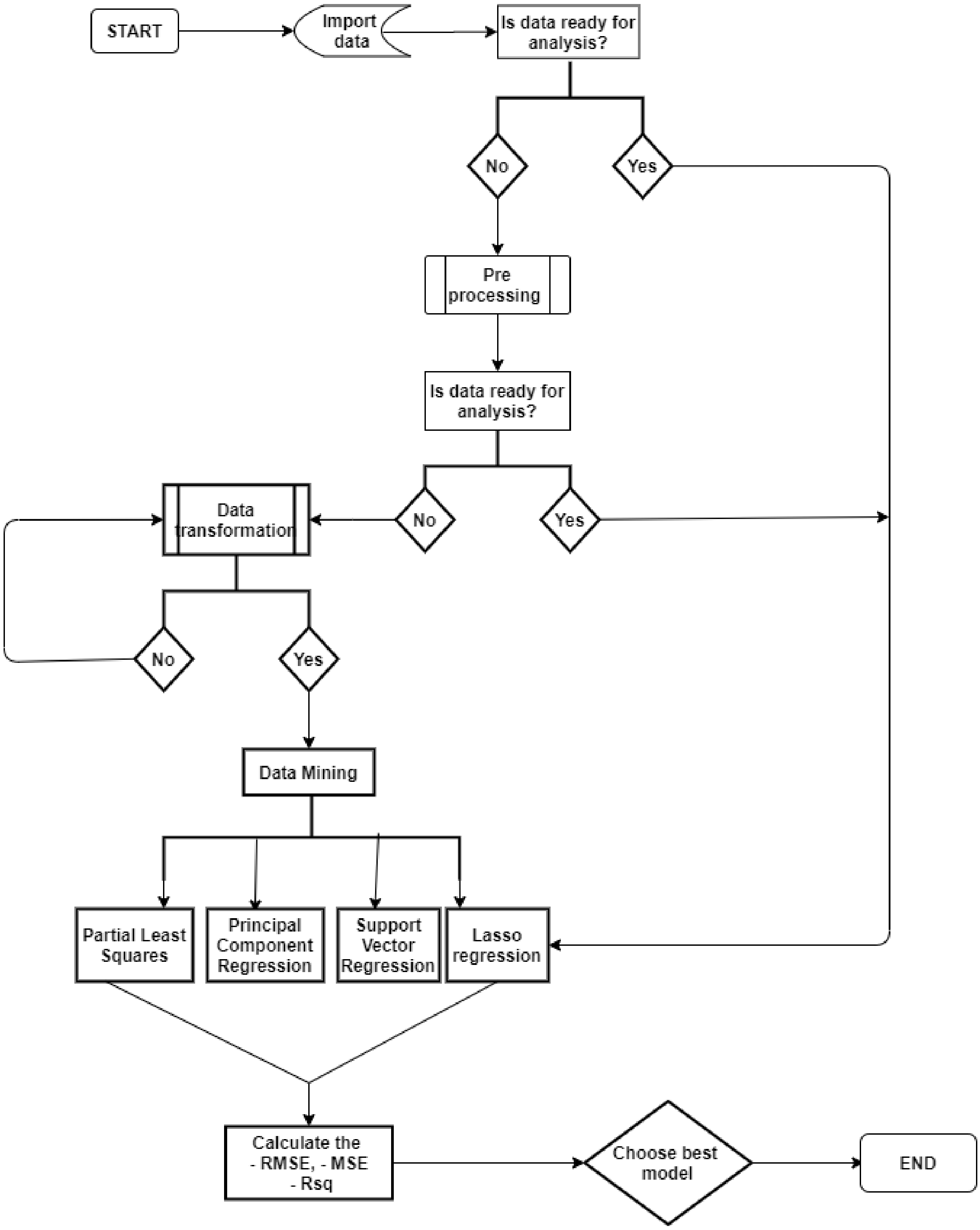
3.3.4 LASSO Regression- Least Absolute Shrinkage Error

Lasso regression is usually used when the variables show some level of multicollinearity. The model addresses this problem by shrinking certain insignificant to the central point pf the variable It does this by penalizing the absolute size of the regression coefficient. In essence, Lasso regression simultaneously carries out variable selection and regularization of the variables.

4 DESIGN SPECIFICATION

This section with the diagram in Fig 2 shows a detailed flow of the processes followed for the analysis. It aims to give a comprehensive approach to the overall methodology adopted. Further explanation of how it is implemented in this research is in **Chapter 5.**

Figure 4: Flowchart showing the design specification of Analysis | Source: Author's



5 IMPLEMENTATION

This section gives a step by step detail on how the analysis was carried out and implemented. It further explores how the KDD methodology and how the three models were built and, these models were chosen as a result of their ability to handle multicollinearity extensively without introducing bias, overfitting, or too much complexity to the final model. The diagram below which constitute the following sub-headings outlines how the analysis was implemented.

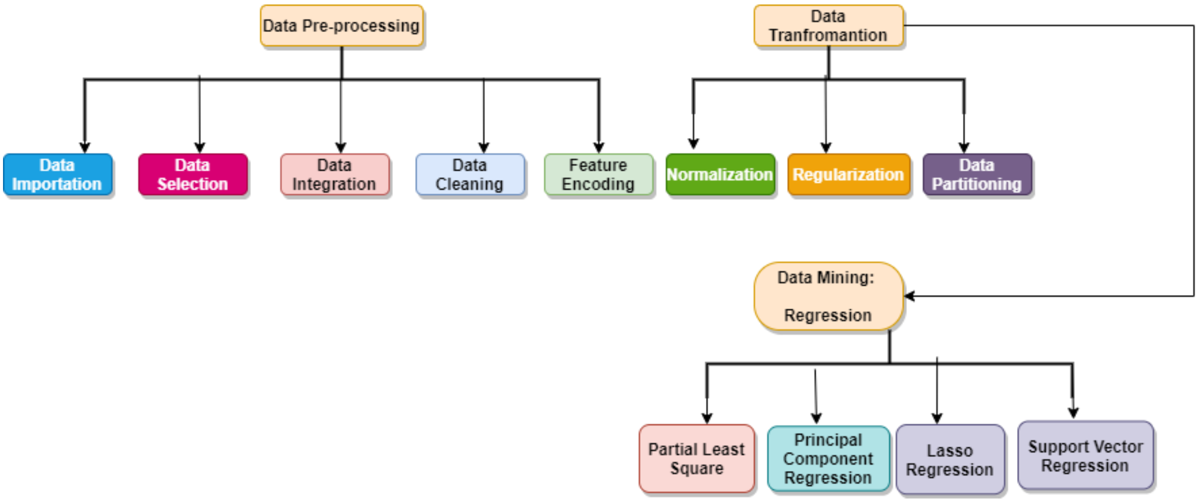


Figure 5: Adopted KDD Methodology (Source: Author)

5.1.1 Data Pre-Processing

This study was carried out with a cross-sectional analysis to evaluate the impact of fintech payment solutions on the GDP of countries in Sub-Saharan. Multiple data pre-processing steps were carried out to eliminate noise and other forms of inconsistencies in the data. They include:

5.1.2 Data Importation

The data sources were imported into R Studio as CSV files using the *read.csv()* function in R.

5.1.3 Data Selection

The data used was formed by extracting columns related to SSA and FPS from the two data sources After relevant columns were selected, the Global Findex data was successfully streamlined to 82 variables which were columns for debit and credit cards, mobile payments, and digital payments. This was merged with the Maddison GDP dataset, this data contained the GDP of countries across multiple continents from 1760- 2016. With over 17000 rows and 5 columns, only SSA countries were extracted as well. This was further streamlined to the GDP of countries between 2011 and 2016.

5.1.4 Data Integration

This step was carried out to merge the two data sources. This was done because the two data sources had the followed variables in common, *'Year', 'Country', 'Region' 'Code'*, therefore using the '*merge'* function in the R package, the data sources were joined. The merged dataset was joined based on years that were mutual to both data set (2011 and 2014). The merged dataset 62 rows and 82 columns.

5.1.5 Data Cleaning

Data cleaning carried out was the imputation of missing values. Due to the high collinearity of the variables, machine learning imputation techniques more specifically MICE an inbuilt R package failed to address as this is one of the shortcomings of the algorithm. The mean imputation technique was then implemented. This step was immediately followed by feature encoding of the categorical variables.

5.1.6 Feature Encoding

The Income Level variable was encoded using the *model. matrix* function in the R package. Before encoding, the different levels include, *low, high, middle-upper middle-lower, middle*. These levels were represented with 0's and 1's therefore automatically converting this variable to numeric variables.

5.2 Data Transformation

This step is pivotal because beyond testing for regression assumptions, it tackled specific challenges that are prerequisites when building regression models. Model diagnostics were carried out on the merged dataset before transformation and the following results were obtained in 5.2.1.

5.2.1 Model Diagnostics

Test for Multicollinearity: multicollinearity is said to be present in a dataset when the independent variables are highly correlated. The pairs graph below shows a high level of multicollinearity. Regularization techniques were used to tackle this. The kappa value of the variables was examined and a rule of thumbs states that a high value of collinearity exists when the Kappa value is above 100. The table below shows the Kappa statistics with a value of 444.90.

Table 1: Test for Collinearity & RMSE Value for Regularization

Test for Collinearity	RMSE Value
Kappa Statistics: 444.9049	RMSE for train data: 0.06 RMSE for test data: 0.09

The pairs graph below shows the pairwise correlation amongst the independent variables.

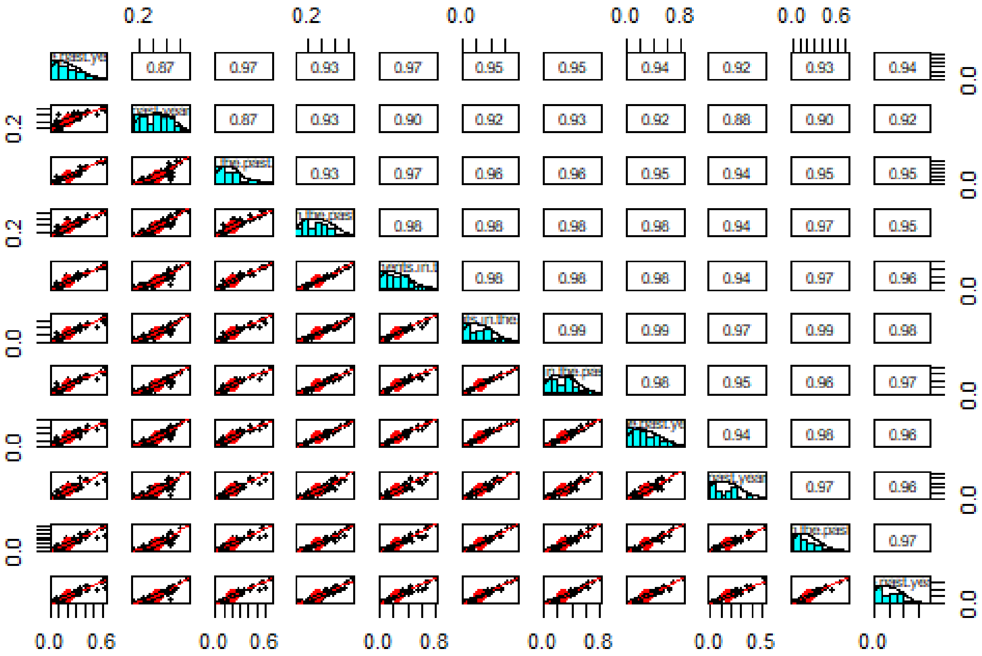


Figure 6: Variable Plot of Dataset

5.2.2 Regularization, Normalization & Partitioning

Elastic Net regression for regularization because its algorithm is built to regularize insignificant variables to 0 while performing feature selection. Carrying out this step resulted in assigning a coefficient to only 23 variables. The image below gives a pictorial view of the variable importance graph showing only variables that can have the most significance on the model to be built.

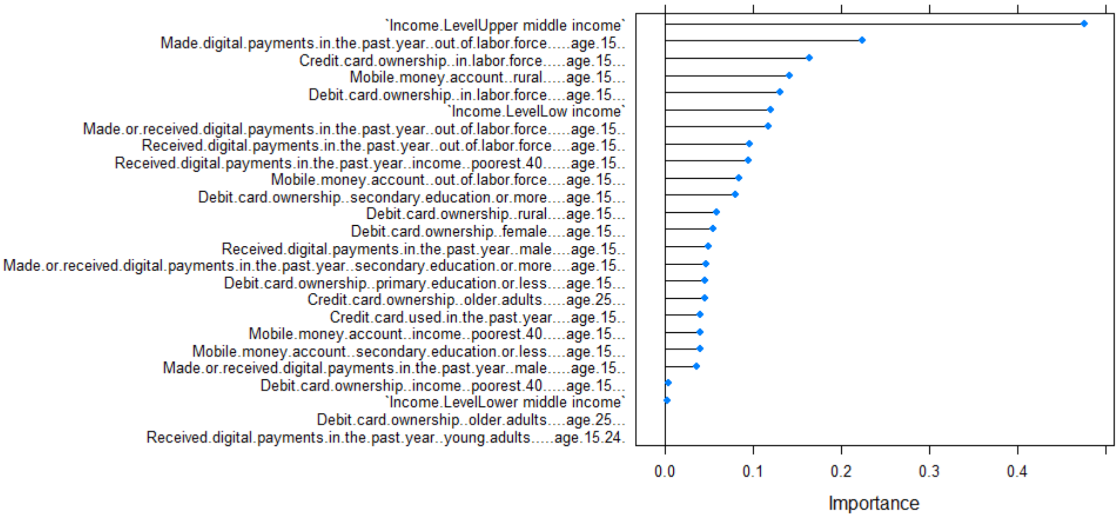


Figure 7: Variable Importance Graph from Elastic Net

Before carrying out the regularization technique and build the elastic net model, the data set was normalized and also partitioned into testing and training set.

5.3 Data Mining & Modelling

The data mining and modeling section give a detailed description of the different data mining techniques and how the models that were built. The modeling and data mining was carried out using R programming via Rstudio. The *pls()* library in R was used to build the

PCR and PLSR models, the *caret()* library was used to build the SVR, and '*glmnet()'* was used for the LASSO model.

The performance metrics for the models include *RMSE, MSE,* and *R-squared*.

i. **RMSE**: commonly used parameter for measuring the error rate in any regression model. RMSE is used to represent the standard deviation of the residuals for the model.
ii. **MSE**: mean squared error is usually calculated by obtaining the square of the error mean of the regression line. It is usually a tradeoff between bias and variance. The smaller the MSE of the regression model the better the model.
iii. $\mathbf{R^2}$: referred to as the coefficient of determination, it is used to describe the proportion of variance of the dependent variable that can be explained by the model built with the independent variables.

6 RESULT & EVALUATION

This chapter discusses the results obtained for the different models while also comparing the models amongst themselves.

Table 2: Performance metrics across all models

Model	MSE (train set)	RMSE (train set)	Rsq (train set)	Rsq (test set)	Relevant Component
PLSR	0.0003	0.017	0.99	0.97	**ncomp = 7**: 81.0
PCR	0.0068	0.083	0.087	0.93	**ncomp = 12**: 87.72
LASSO	0.01	0.1	-	0.84	**lamda**: 0.01
SVR	0.00049	0.0222	0.99	-1.95	**gamma**:0.017

Table 2 above shows the overall performance using different metrics for the models built. The '*relevant component'* column highlights the unique metric characteristics for each model.

Examining the results of the PLSR model, we can see that the error rates for the model measured with MSE and RMSE recorded as 0.0003 and 0.017 are significantly low. This implies that the model built performed quite well because of the low error rates. These low error rates are then reinforced by the R^2 of 97%. This implies that 97% of the variance of the dependent variable from the test dataset is described by the model. Additionally, the PLSR model attained this level of high accuracy by using only 7 components (ncomp). Statistically, it is advised to adopt the model that can obtain a reasonable level of variable explanation (> 80%) using the least number of components. However, the PCR model used 12 of its component and as expected it doesn't perform well as the PLSR. The accuracy, R^2 of 93% implies that the model still performs well when predicting the dependent variable – GDP. The error rates of this model, MSE/RMSE of 0.068 and 0.083 respectively, although not as low as PLSR it is low enough to be considered as a good model for the prediction of Y.

Interestingly, the SVR model is the least performing model because its R^2 has a negative value meaning that the model is predicting against the values. Hence, there is no impact or relationship amongst the variables. This finding makes it clear and evident that the SVR's approach to handling regression problems without dimensionality reduction of highly correlated data should be greatly avoided. These results are then concluded with the LASSO regression technique. From the R^2 of 84%, it can be concluded that it is the third best performing model. The model also records low error rates of 0.01 and 1 in its MSE and RMSE respectively. This cannot be compared to the other models with lower error rates, however, the model seems to be predicting the values of Y at a fair rate.

6.1 MODEL VISUALS EVALUATION

This section goes further to give a visual representation of the accuracy level, error rates, and the relevant coefficient table of the different models built.

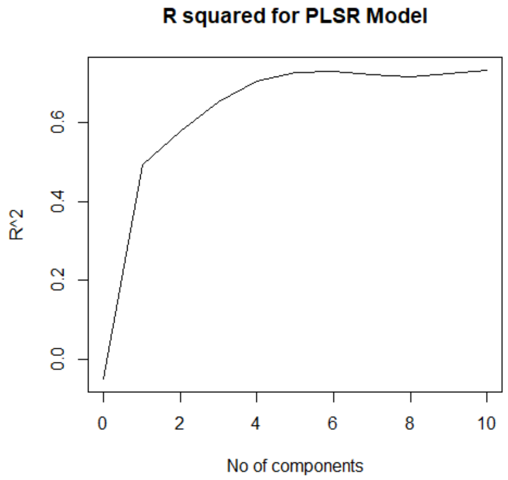


Figure 8: Graph of the accuracy of PLSR Model

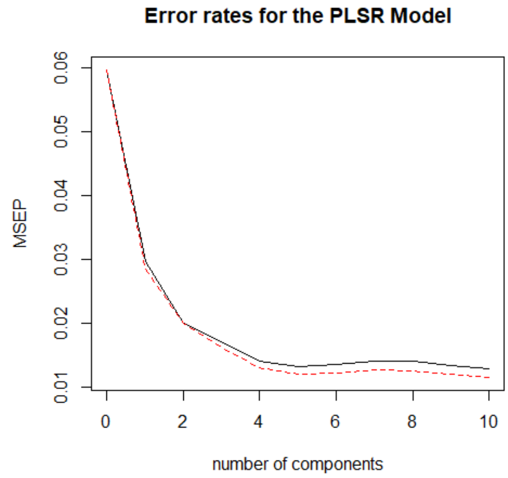


Figure 9: Error rates if the PLSR Model

Figures 8 and 9 show the accuracy and error rates of the PLSR model. It is noticed that the model as initially stated from table 2 above performed well with a low number of components. The performance level of the model at 10 components is almost equivalent to its accuracy at 7 components. Therefore, this is the rationale behind which this number of components was used for the final model. The complementing error graph in Figure 9 shows that the error rate remained reasonably stable between 5-7.

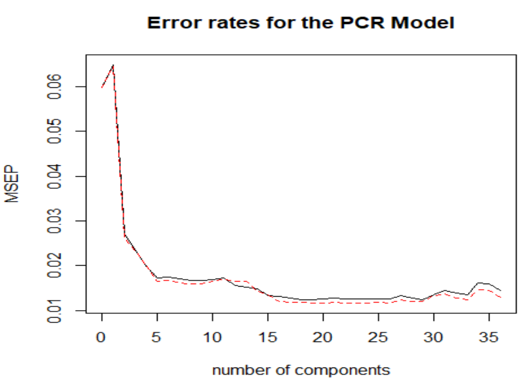


Figure 10: Error rates for PCR Model

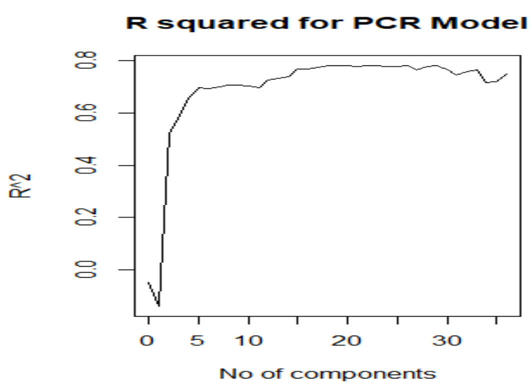


Figure 11: Accuracy Plot for PCR Model

The graphs in Figures 10 and 11 are closely related to the graphs in figures 3 and 4. This result is particularly interesting because it validates the claims that PLSR is an improved adaptation of PCR. From figure 5 we can conclude an optimal model is built if ncomp is between 12 – 20.

The table below shows the different coefficient obtained from running the lasso model. An advantage this model has over other models is its ability to show the individual impact of the different variables. Due to its ability to shirk insignificant components, the lasso model revealed the different areas of Fintech payment with the most relevance and impact on the model built These results are further discussed in **section 6.2.**

Table 3: Variable Coefficient Relevance from Lasso Model

Relevant Variables	Coefficient
Received.digital.payments.in.the.past.year	0.0003669963
Credit.card.ownership	0.0202080379
Debit.card.ownership..secondary.education.or.more	0.0514985728
Debit.card.ownership..in.labor.force	0.5904636402
CountryNigeria	0.0742816504
CountryMauritius	0.142708231
CountryGabon	0.1220624441

6.2 DISCUSSION

This study contributes to the growing research going on within the Fintech industry as it explored a rather new domain in this industry. The main contribution of this research is to serve as a guide to policymakers, investors, and entrepreneurs on the growing aspect of fintech payments in SSA. The regression models built were used to estimate the level of impact of fintech payment solution on the GDP of selected countries. While carrying out this analysis, it is essential to note that other variables affecting GDP have been assumed to be constant.

This research is one of the first to evaluate fintech payment solutions from an analytical perspective. Theoretically speaking, the results obtained in line with the hypothesis made, showed that indeed fintech payment solutions have an impact on the economic growth of selected countries. This is in line with the conclusions from (Ajiboye et al., 2013). The measure of accuracy in terms of impact in this research was the R-squared regression parameter which was used to prove that a significant relationship exists between GDP and the independent variables. Critically examining table 3 it is evident that card payments generally topped the list in terms of usage for countries within SSA. This claim is supported by Amromin and Chakravorti, (2007). Although credit cards are not a very common form of payment in SSA, it is beginning to gain some level of attention as fintech solutions get embraced.

An undesirable and unexpected result obtained was that the model did not highlight mobile payment as one of the key contributors to GDP in SSA. The inability to highlight this leads to a contradiction of what other scholars have written. But the results however showed that access and use of digital payments are significant in SSA and several reviewed articles usually categorized mobile payments as digital payments. This subtle yet relevant result can be attributed to the regularization done during transformation and the shrinkage functionality in the Lasso model. Interestingly and unpopular to researchers, there has been growth for fintech firms in terms of payment solutions in Gabon. Although low in terms of numbers, this is certainly noteworthy as it portrays what the future might hold for Gabon This is supported by the research carried out by BNP Paribas in “GABON,” (2017.). Beyond this similar to other academic research, the impact of fintech payment solutions in Nigeria has been immense over the last couple of years. There is research regarding the country transitioning to become a cashless economy through Fintech payments.

7 Conclusion & Future Work

This research focused on examining if an increase in the adoption rate of FPS leads to an equivalent increase in the GDP of EMs in SSA. The investigation was carried using four regression models. Contributing to the growing body of knowledge studying relevant fintech sectors, this research evaluated the impact of FPS across four subsections and they include debit and credit card payment, mobile payment, and digital payment. Out of the regression models built (SVR, PLSR, PCR, and Lasso), PLSR was the best performing and this was followed by PCR. The basis of judgment was determined by the R^2 and RMSE of the models. The findings obtained were in two folds. First, the more FPS is used within a country, the higher its GDP. Secondly, digital payments as well as debit card payments are two very promising areas of FPS in EM within SSA. A drawback in the models remains its inability to identify the immense contribution of mobile payments in SSA. Like every other research, some of the limitations faced include the unavailability of comprehensive data across multiple years. Carrying out a panel study of these FPS will enable the models to obtain a more realistic result because analyzing the adoption rate of payments requires a behavioral study of the individuals responding to the data to be used.

The results obtained from this research certainly motivate some areas for future research. To begin with, researchers can explore beyond the outlined FPS as payment solutions like cryptocurrencies and virtual payment cards are beginning to interest academicians. In addition to this, researchers should investigate the use of these payment solutions from a gender perspective as this will give in-depth analysis as to whether FPS is dependent on the gender of the individual in question. This research can serve as a take-off point to begin tackling FI in EMs as FI starts first and foremost with access to and usage of payment services.

Finally, considering that industries are experiencing significant downturns due to the COVID-19 pandemic, it is only essential for investors to seek assets that will give the most optimal value for their resources. This goal is what this research intends to achieve, to help those actively investing within the fintech industry see the most prominent sectors.

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