Fintech Predictive Modeling and Performance of Investment Firms in Kenya

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Abstract

Predictive analytics is concerned with the prediction of future trends and outcomes. The approaches used to conduct predictive analytics can be classified into machine learning techniques and regression techniques. This study dteremined the influence of fintech predictive modeling on performance of investment firms in Kenya. The study population was 57 investment firms. The study employed mixed method research design by incorporating descriptive and explanatory research designs. Data was collected using questionnaires and an in-depth interview guide. Coefficient of fintech predictive modeling has a positive and significant effect on performance of investment firms. The study concluded that fintech predictive modeling allows investment firms to forecast business growth and customer behaviour chnages. It is important for an investment firm to be able to understand business growth by accurately forecasting future growth and survival. Moreover, it is of vital necessity to understand changes in customer buying/consumption behavior so as to develop products and services that suit their needs and preferences. As a result, predictive modeling is required to project future business growth and changes in customer consumption pattern.

Keywords

Fintech Predictive Modeling, Performance of Investment Firms, Kenya.

Introduction

Predictive analytics helps in predicting future business trends and outcomes. The techniques used in conducting predictive analytics include machine learning mechanisms and regression mechanisms (Nassif, 2015). Predictive modeling technologies uses algorithms trained with vast amounts of data to improve operational efficiency and financial performance of a firm. Predictive analytics is concerned with the prediction of future trends and outcomes. The approaches used to conduct predictive analytics can be classified into machine learning techniques and regression techniques (Nassif, 2015). Machine learning techniques have become increasingly popular in conducting predictive analytics due to their outstanding performance in handling large scale datasets with uniform characteristics and noisy data (Zerucha, 2016). Innovative predictive models have been applied successfully in several domains such as health care, cyber security, education, credit card fraud detection, social media, cloud computing, software measurement, quality and defect prediction, cost and effort estimation and software reuse. Some of predictive techiques include scoring technigues, data analsyiscs and cognitive computing.

Scoring techniques measures clients' credibility worthiness while predicting individual probability to make credit payments on time (Waller & Fawcett, 2013). Predictive modeling is popular in doing predictive analytics because of its ability to handle large sets of data with similar features (Zerucha, 2016). Data analytics techniques are employed in doing risk monitoring in order to check compliance. Predictive analytics also serve as mechanisms used in information management, estimating transaction reports and regulatory reports (Erman, 2017). While predicting assets behavior in financial modeling, Esteves and Duarte (2013) found that predictive modeling facilitates asset visualization in a firm. By adopting quantitative research design to establish how fintech is changing the world, Truong (2016) identified critical roles of machine learning predictive analytics in financial modeling and management. Predictive modeling is used to model firm's future financial performance.

Predictive analytics capture the parsing of vast databases containing the characteristics and transactions of billions of economic agents through advanced algorithms to derive patterns used to predict behavior and prices, and in the end mimic human judgment in automated decisions (Schaus, 2016). Related applications can automate credit approvals or advice, facilitate regulatory compliance and fraud detection, and automate the trading of financial assets.

Data analytics tools can be used for continuous risk monitoring and analysis as mean to enhance compliance. These technologies could serve as tools for information management as well as transactions reporting and regulatory reporting. For example, they can be used to identify virtual currency wallets associated with "bad actors" based on common technical information or transaction patterns (Erman, 2017). By identifying these wallets, public authorities will be able to identify which transactions involve illicit activities. Absent these tools, the analytics of increasing larger datasets would entail significant costs in time and labor with an added risk of human errors and omissions (Munohsamy, 2015).

Cognitive computing and artificial intelligence technologies enable data mining algorithms based on machine learning which can organize and analyze large sets of data. Machine learning can create self-improving and more accurate methods for data analysis, modeling and forecasting as needed, for example, for stress testing (Geranio, 2017). Machine learning predictive analytics enable the treatment of regulatory content as data, further permitting to manage it programmatically. These technologies may eventually be applied to track regulatory changes and even interpret new regulations.

In Kenya, research work on the fintech industry and digital revolution is also scarce in spite of witnessing the most rapid financial evolution of all time since 2007 when M-Pesa entered the market (Misati, *et al.*, 2019). Besides the developments in the mobile industry, credit-only institutions have equally blossomed in Kenya. Riding on advanced technology, both the mobile financial services and the credit-only institutions have progressively transformed payment services into cashless (mobile wallet) and invisible given their heavy reliance on non-brick and mortar relationships. Fintech services have led to the rapid emergence of financial application mobile apps in Kenya. Some of the notable mobile money solutions that have been launched include; M-Shwari, M-Co-op Cash, KCB M-pesa, M-kopa (Tala), Branch, Eazzy loan, Timiza, among others. Indeed, there is evidence to attest to the fact that new partnerships led to increase in the new accounts opened in the period 2012 to 2015, (IFC, 2017). As pointed out by Totolo, (2018), since the introduction of M-Shwari in 2012, which offers savings account and digital credit, the market for digital credit has expanded substantially beyond commercial banks to fintech firms and non-bank institutions. This study determined the influence of fintech predictive modeling on performance of investment firms in Kenya. The hypothesis is; fintech predictive modeling has no significant influence on performance of investment firms in Kenya.

Literature Review

This paper is guided by the mean variance-portfolio theory. Mean variance-portfolio theory by Markowitz (1959) assumes that investors must make a balance between risks and returns of a proposed investment. The theory maximizes return by cautiously selecting different portfolios. It is widely used in practice in the financial industry (Markowitz, 2009). A right combination of different assets maximizes returns (Sirucek & Křen, 2015). MVPT states that it is not enough just to look at the expected risk and return of one particular stock. By investing in more than one stock, an investor can obtain the benefits of diversification, a reduction in the volatility of the whole portfolio (Markowitz, 1959). The MVPT is a theory of investment which attempts to maximize portfolio expected return for a given amount of portfolio risk, or equivalently minimize risk for a given level of expected return, by carefully choosing the proportions of various assets. Mean variance-portfolio theory is widely used in practice in the financial industry (Markowitz, 2009).

The MVPT is a sophisticated investment decision approach that aids an investor to classify, estimate, and control both the kind and the amount of expected risk and return (Omisore, Yusuf & Christopher, 2011). Essential to the portfolio theory are its quantification of the relationship between risk and return and the assumption that investors must be compensated for assuming risk (Sirucek & Křen, 2015). By combining different assets whose returns are not perfectly positively correlated, MVPT seeks to reduce the total variance of the portfolio return. MVPT also assumes that investors are rational and markets are efficient. The fundamental concept behind the MVPT is that assets in an investment portfolio should not be selected individually, each on their own merits. Rather, it is important to consider how each asset changes in price relative to how every other asset in the portfolio changes in price (Rani, 2012).

The theory is applicable to this study as it highlights the need for asset portfolio modeling. An investment firm is able to choose the best portfolio through fintech. By using fintech, investment firms are able to manage their assets. Risk takers firms are able to invest in emerging financial technologies. Financial technologies that include block chain, peer to peer lending and machine learning predictive analytics can make turnaround for the investment firms by improving efficiency, payment mode, reducing cases of fraud while fostering financial growth.

By using advanced algorithms predictive modeling to predict behavioral trend and prices to facilitate automated decisions Schaus (2016) established that there is a significantly growing role of fintech in the modern economics and suggested the need to digitize business operations. Similarly, systems help automating credit approvals, facilitating fraud detection, and automating the trading of financial assets (Khan & Khan, 2011). Predictive analytics helps in predicting future business trends and outcomes. The techniques used in conducting predictive analytics include machine learning mechanisms and regression mechanisms (Nassif, 2015). Predictive modeling technologies uses algorithms trained with vast amounts of data to improve operational efficiency and financial performance of a firm.

Scoring techniques measures clients' credibility worthiness while predicting individual probability to make credit payments on time (Waller & Fawcett, 2013). Predictive modeling is popular in doing predictive analytics because of its ability to handle large sets of data with similar features (Zerucha, 2016). Data analytics techniques are employed in doing risk monitoring in order to check compliance. Predictive analytics also serve as mechanisms used in information management, estimating transaction reports and regulatory reports (Erman, 2017). While predicting assets behavior in financial modeling, Esteves and Duarte (2013) found that predictive modeling facilitates asset visualization in a firm. By adopting quantitative research design to establish how fintech is changing the world, Truong (2016) identified critical roles of machine learning predictive analytics in financial modeling and management. Predictive modeling is used to model firm's future financial performance.

Predictive analytics is concerned with the prediction of future trends and outcomes. The approaches used to conduct predictive analytics can be classified into machine learning techniques and regression techniques (Nassif, 2015). Machine learning techniques have become increasingly popular in conducting predictive analytics due to their outstanding performance in handling large scale datasets with uniform characteristics and noisy data (Zerucha, 2016). Innovative predictive models have been applied successfully in several domains such as health care, cyber security, education, credit card fraud detection, social media, cloud computing, software measurement, quality and defect prediction, cost and effort estimation and software reuse. The hypothesis (H_{04}) tested is; fintech predictive modeling has no significant influence on performance of investment firms.

Using qualitative and Delphi method approach Lee, Jang and Park (2017) predicted that the performance of investment firms was influenced by the ability of the firm to predict future business trends. To estimate impact of predictive modeling on business profitability, Andrés, Lorca and Bahamonde (2004) found that predictive modeling helped in forecasting customer behavioral trends, trend of price, change in taste and preference and financial growth. In another study on data and information visualization methods, Khan and Khan (2011) found that information visualization methods significantly helped companies in predicting investment outcomes. However, the study failed to measure effects brought by information visualization on firm' performance.

Soriano (2017) undertook a study on factors driving financial inclusion and financial performance in Fintech new ventures. Primary data was collected from 63 Fintech startups from Southeast Asia, India and Africa and ran multi-variate regression and binomial logit models to quantify the main effects of these factors. The results showed that founders with prior financial services experience, the degree of customer centricity in the firm's business model, and strategic partnerships with financial institutions and e-commerce firms, had a significant and positive correlation with financial inclusion (as measured by Active Customers) and financial performance (as measured by Annual Revenue). A qualitative analysis of 4 Fintech startups from the data sample demonstrated that other factors such as scalability, prior startup experience, and type of product sold (pull vs. push) are also critical to the startups' success, and provide insights for further empirical research. The study did not indicate how fintech services influence firm performance.

Research Methodology

The study employed descriptive and explanatory research designs. The target population was 57 investment firms that have integrated fintech in their business operations. A census of all the 57 investment firms was conducted. Primary data were collected using a structured questionnaires and in-depth interview guide. Qualitative data were analyzed using content analysis technique. Content analysis categorizes phrases, describe the logical structure of expressions and ascertain associations, connotations, denotations, elocutionary forces and other interpretations. Quantitative data was analyzed using inferential statistics specifically the structural equation modeling (SEM).

Research Findings and Discussion

Data analysis entailed structural equation modeling. SEM results as shown in Table 1 show that the influence of fintech predictive modeling on performance of investment firms is significant (R^2=.817, $p<0.05$), implying that 81.7 percent of variation in performance of investment firms is explained by fintech predictive modeling.

Table 1 Influence of Fintech Predictive Modeling on Performance of Investment Firms

			Estimate	S.E.	C.R.	P-value
Firm performance	<---	FPM1	.232	.074	3.121	.002**
Firm performance	<---	FPM2	.033	.069	.481	.631
Firm performance	<---	FPM3	.075	.055	1.373	.170
Firm performance	<---	FPM4	.434	.105	4.148	.001**
Firm performance	<---	FPM5	.046	.044	1.045	.296
Firm performance	<---	FPM6	.156	.077	2.028	.043*
Firm performance	<---	FPM7	.229	.057	4.024	.001**
Firm performance	<---	FPM8	.008	.048	.165	.869
Firm performance	<---	FPM9	.100	.039	2.534	.011*
Firm performance	<---	FPM10	.044	.037	1.189	.234
Firm performance	<---	FPM11	.196	.055	3.529	003**

	Estimate
Squared correlation	.814

**Significant at 0.05

Where
FPM1= Investing in new risk pools is helping the firm counter attack fraudsters
FPM2= Sensors technologies are helping the firm to quickly verify documents.
FPM3= Predictive modeling is helping the firm generate investment advice.
FPM4= Predictive modeling technology is making the firm do credit decisions faster and easily.
FPM 5= Predictive modeling is facilitating fraud detection in the firm.
FPM 6= Predictive modeling is making asset trading quick and reliable.
FPM 7= Predictive analytics is helping the firm predict the trend of future prices and customer behavior.
FPM 8= Predictive analytics is helping the firm process large amount of data with uniform and noisy characteristics.
FPM 9= Data analytics tools are helping the firm model business risks.
FPM 10= Cognitive computing is allowing firms analyze large sets of data in short time.
FPM11= Predictive analytics is helping firms track regulatory changes and even interpret the new regulations.

Model results indicate that the coefficient of the statement that investing in new risk pools help firm counter attack fraudsters is positive and significant (β=.232, P<0.05) with firm performance. The beta coefficient of.232 suggests that a unit change in the investment in new risk pools with high returns leads to.232 units change in performance of investment firms. The coefficient of the statement that sensors technologies in quickly verifying documents and performance of investment firms have a positive but insignificant relationship (β=.033, P>0.05). The coefficient of the statement that predictive modeling has helped the firm generate investment advice also has a positive but insignificant relationship (β=.075, P>0.05) with firm performance.

The coefficient of the statement that predictive modeling technology is making the firm do credit decisions faster and easily is positively and statistically significant with performance of investment firms (β=.434, P<0.05) implying that a unit increase in the use of predictive modeling technology to do credit decisions faster leads.434 unit increase in performance of investment firms. The coefficient of the statement that predictive modeling is facilitating fraud detection in the firm is positively but significantly related with firm performance (β=.046, P>0.05). Further, the coefficient of the statement that predictive modeling is making asset trading quick and reliable has a positive and significant (β=.156, P<0.05) relationship with performance of investment firms implying that a unit increase in the use of predictive modeling in quickly and reliably undertaking asset trading results with.156 unit change in the performance of investment firms.

The coefficient of the statement that predictive analytics is helping the firm predict the trend of future prices and customer behavior has a positive and significant relationship with performance of investment firms (β=.229, $P<0.05$) implying that the ability of a firm to predict future business trends helps it plan and make desirable investment decisions hence higher performance. The coefficient of the statement that predictive analytics is helping the firm process large amount of data with uniform and noisy characteristics has a positive but insignificant relationship with performance of investment firms (β=.008, $P>0.05$).

The coefficient of the statement that use of data analytics tools to model business risks is positive and statistically significant with performance of investment firms (β=.100, $P<0.05$) implying that unit increase in the use of data analytics tools to model business risks results to.100 unit improvement in performance of investment firms. However, the coefficient of the statement that use of cognitive computing to analyze large sets of data in short time is positively but statistically insignificantly related to performance of investment firms (β=.044, $P>0.05$). It was also found that the coefficient of the statement that use of predictive in track regulatory changes and even interpret the new regulations. is positively and statistically significant with performance of investment firms (β=.196, $P<0.05$) implying that unit increase in the use of predictive in track regulatory changes results to.196 unit improvement in performance of investment firms.

Coefficient of fintech predictive modeling is positively and significantly related to performance of investment firms. Fintech payment techniques are significant predictor performance of investment firms. The null hypothesis that fintech predictive modeling has no significant influence on performance of investment firms in Kenya was rejected and conclusion made that fintech predictive modeling influences performance of investment firms. In an interview session with investment managing director 2, he had this to say;

"…predicting modeling allows a firm to predict customer behavioral changes and growth of business. Scoring techniques measures clients' credibility worthiness while predicting individual probability to make credit payments on time. Data analytics techniques are employed in doing risk monitoring in order to check compliance. Predictive analytics also serve as mechanisms used in information management, estimating transaction reports and regulatory reports." Managing Director 2 [Key Informant, 2019].

Predictive modeling can be employed by an investment firm to predict customer behavioral trend and prices to facilitate automated decisions. Predictive analytics helps in predicting future business trends and outcomes. Similarly, predictive modeling help automating credit approvals, facilitating fraud detection, and automating the trading of financial assets. The results agree with Khan and Khan (2011) that information visualization methods significantly helped companies in predicting investment outcomes. Predictive modeling technologies uses algorithms trained with vast amounts of data to improve operational efficiency and financial performance of a firm. Scoring techniques measures clients' credibility worthiness while predicting individual probability to make credit payments on time. Predictive modeling is popular in doing predictive analytics because of its ability to handle large sets of data with similar features. The results concur with Esteves and Duarte (2013) that predictive modeling facilitates asset visualization in a firm. The results also agree with Truong (2016) that predicting modeling plays a critical role in financial modeling and management. Predictive modeling is used to model firm's future financial performance. According to Jang and Park (2017) a firm is able to predict future business trends. Moreover, Andrés, Lorca and Bahamonde (2004) noted that predictive modeling helped in forecasting customer behavioral trends, trend of price, change in taste and preference and financial growth.

Conclusion and Recommendations

The study concluded that fintech predictive modeling allows investment firms to forecast business growth and customer behaviour chnages. Predictive modeling involves the analysis of large datasets to make inferences or identify meaningful relationships and the use of these relationships to better predict future events. It uses statistical tools to separate systematic patterns from random noise, and turns this information into business rules, which should lead to better decision making. Moreover, change in customer consumption behavior can be modeled using fintech predictive technologies. Fintech predictive modeling help investment firms design and implement a financial analytics solution in order to improve business growth forecast accuracy. As part of the scope, predictive modeling, provide strategic advice to the internal clients, and transform how they interact with their clients through leveraging dynamic and interactive dashboards, rather than the conventional excel-based and paper-based approach. Predictive analytic techniques, credit scoring models and other sophisticated statistical models are often employed by financial institutions to understand and manage the risk of their loans and lending portfolios.

The use of fintech services demands sufficient financial resources. However, it was concluded in the study that the allocation of financial resources to fintech services among majority of investment firms is not sufficient. Sufficient financial resources are required to acquire various fintech services, install the fintech services, periodically update the systems, and maintain the systems. Moreover, lots of financial resources are required to pay fintech specialist and experts that operate and maintain fintech services.

It is important for an investment firm to be able to understand business growth by accurately forecasting future growth and survival. Moreover, it is of vital necessity to understand changes in customer buying/consumption behavior so as to develop products and services that suit their needs and preferences. As a result, predictive modeling is required to project future business growth and changes in customer consumption pattern. The study recommends that investment firms may consider expanding the use of predictive modeling techniques to include businesses survival analysis methods in forecasting business growth in order to make informed investment decisions. The techniques may include use of businesses survival analysis methods to project business existence and using machine learning algorithm to predict customer future consumption pattern. Fintech predictive modeling methods can also be employed to detect impending financial fraud in an organization.

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