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Modelling credit risk using system dynamics: The case of licensed credit reference bureaus in Kenya

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Abstract:

Credit reference bureaus (CRBs) have been operational in Kenya for many years owing to the large number of borrowers who fail to repay their loans. However, regulating how credit risk will be quantified by these CRBs is often based on standards and assumptions that are not practical to the real-world scenario. This study models credit risk to discover more effective and practical measures which relate to the borrowers and their operating environment. Data was collected from annual default reports from the Central bank of Kenya, CRBs and major financial institutions over a period of three years (2018, 2019, and 2020). The study also used focus group discussions to establish the key default factors and their baseline values. A sample of 29 participants was drawn from the population of CRB staff members who undertake the core functions of credit risk determination. Using the system dynamic modeling and simulation approach, the study identified faithful representations of default risk measurements. First, descriptive analysis was conducted using tabled summaries and bar charts and results identified customer income, issued loans and collateral amount as the most influential factors for credit risk. Explorative analysis applied causal loop diagrams (CLDs). Simulation analysis was then conducted after generating stock-and-flow diagrams and three important variables were identified, i.e., loan repayment, performing loans, and credit risk. The information gained from this study will benefit the government, the Central bank of Kenya (CBK), research scholars and other major financial institutions around the country.

Keywords: *Credit risk, Default, Kenya, Simulation, System dynamics modeling*

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1. INTRODUCTION

Many financial institutions in Kenya experience high credit risk since they grant credit facilities as exclusively based on customers' deposits. According to the Basel Committee of Banking Supervision, credit risk is the probability of a financial institution losing an outstanding loaned amount either partially or in full because of default [1].

The supervision annual reports for Kenya show that the ratio of non-performing loans (NPLs) to gross loans increased from 4.7 percent in December 2012 to 5.2 in December 2013, and further to 5.6 in December 2014 [2]. By December 2018 the NPLs ratio had grown to 12.7 percent [3]. These supervision reports also indicate a decreased capital adequacy within the Kenyan financial sector, a factor that is calculated as the ratio of total capital to total risk-weighted assets within a specific financial year. The increase in non-performing loans, inefficient loan processing by financial institutions, unwarranted interference with the loan granting process, and insufficient and/or absent loan collaterals are among the factors that have been linked to poor and unproductive management of credit. High credit risk has in turn caused a lot of negative impacts on the performance of banks and other financial institutions in Kenya. The deteriorating economic situation caused by the Coronavirus disease 2019 (COVID-19) pandemic also resulted in a large proportion of Kenyans being barely capable of meeting their basic needs and unable to repay their existing debts [4]. This study, therefore, sought to investigate the credit risk factors influencing the performance of Kenyan financial institutions in contribution to the existing knowledge on credit risk.

The general objective of this study was to apply a system dynamics approach to model and simulate credit risk for licensed credit reference bureaus in Kenya. Specifically, the study sought answers to the following research questions.

- *Which are the factors that influence credit risk from individuals and businesses in Kenya?*
- *How can these factors be modeled using a system dynamics approach?*
- *To what extent is the developed credit risk determination model applicable to the real-world context?*

2. LITERATURE REVIEW

This section reviews the literature on credit risk modelling to understand existing approaches and the research gaps, and to identify the best practices in modelling credit risk.

2.1. Credit Risk Management in Kenya

Credit risk is the risk that financial institutions face during resource allocation because of non-payment or delayed payment by borrowers. Customers with an increased probability to repay a loaned amount are classified as "good customers" while customers with an increased probability to default are classified as "bad customers" [5]. Modelling credit risk assessment is an approach that is crucial for financial institutions because it allows these institutions to ensure that customers are able to pay their instalments, i.e. be classified as "good customers" before allocating a loan facility to them [6].

With the emergence of credit reference bureaus (CRBs) in Kenya, lending processes have been significantly transformed to improve the performance of financial institutions [7]. A CRB is an information broker that seeks to provide dependable, appropriate, and comprehensive data on repayment habits and current credit levels of loan applicants [8]. This data is consolidated from creditors of all forms and packaged on demand into individual-report style for distribution to creditors at a fee. While CRBs support faster and more effective decisions, a recent survey study in Kenya found out that some financial institutions did not consider CRBs to be effective in significantly reducing credit risk [7]. The Annual Supervision report by the Central Bank of Kenya also confirms that non-performing loans (NPLs) remain high, despite the presence of CRBs. One explanation to the inadequate credit risk prediction is the non-linear nature of factors in the credit ecosystem. As a result, the problem of credit risk scoring is not a linear problem, but a highly complex and dynamic problem [5]. Examination of the emphasis placed on credit risk modeling and the management by financial institutions and CRBs in Kenya begs the question, "Is the current practice of credit risk management effective for Kenyan commercial banks and financial institutions?" Given the high credit risk that these institutions continue to face, it is necessary to complement the current measures of credit risk determination approaches which incorporate uncertainty in the measurement process.

2.2. Theoretical Framework

Analysis of credit risk is a pattern-recognition problem which incorporates functions to predict the possibility that a customer will repay a loaned amount [9,10]. Consequently, the key features of any credit risk model are resolution and accuracy. Several methods exist for credit risk modelling and analysis, such as descriptive techniques which provide summarization of data to lay the analytical foundation for data pre-processing [11], data mining and artificial intelligence systems that reveal the patterns in complex data [12], and system dynamics modelling and simulation techniques which account for dynamism and uncertainty in customer behaviour [13]. Table 1 shows the attributes that make system dynamics the ideal methodology for this research.

Elements of system dynamics modelling (SDM) comprise causal loop diagrams (CLDs), stock and flow diagrams, and simulation graphs. Causal loop diagrams are an important tool for representing the feedback structures of systems. They help to 1) construct and test hypotheses about the causes of dynamics, 2) elicit and describe mental models of individuals and teams, and 3) communicate the important feedback processes believed to be causing a systemic problem [21]. Causes, effects and feedbacks are depicted and visualized through CLDs. Therefore, a CLD can be crucial for representing a socio-economic, political, or mechanical system as depicted from a mental model.

Stock-and-flow diagrams extend CLDs by modelling the rate of change among variables. This is because changes in one variable can progressively affect changes in another related variable over time. The stock-and-flow diagram uses a type of variable called a stock (or level of accumulation) whose values flow into another stock at a predetermined rate via another variable called a flow or rate. This allows the model to be calibrated by changing initial values for a stock, or the amount of flow into or out of the stock and conducting a simulation. Results of a simulation can then be mapped using graphs [22].

2.3. Knowledge Gap

Most models of financial credit risk have been designed and developed through trial and error and hence lack a proper theoretical framework [9]. Because of this, the models are not tried and tested, and are unable to perform efficiently in times of economic or political crisis. Many prediction models will typically show high prediction capability, but only under perfect and stable conditions. They, thus, cannot be effectively used in developing countries or in similar scenarios that face a lot of socioeconomic uncertainties [23]. Additionally, ARIMA (autoregressive integrated moving average) models which are commonly used to model financial situations assume normal distribution, but large gains and losses always exhibit higher probabilities than the normal distribution can model [24]. Therefore, such models might be able to function well under optimum financial conditions, but the lack of responsiveness to the evolving environment renders the models inefficient, particularly in the event of concept drifts. Dynamic models that can easily accommodate new factors, changing factors and uncertainty have not been developed for use by CRBs in Kenya.

Table 1. Proposed credit risk modelling techniques.

Focus	Technique	Nature	Predictor	Ref.
Ghana rural banks	Panel regression	Dynamic	Certainty	[14]
Nigerian commercial banks	Augmented Dickey Fuller (ADF), Pairwise Granger causality	Dynamic	Certainty	[15]
Firms in Tehran stock exchange	Neural networks analysis, Self-Organizing Map	Constant	Certainty	[16]
India Banks	Panel data analysis	Dynamic	Certainty	[17]
Kenya microfinance banks	Multiple regression	Constant	Certainty	[18]
Kenyan banks	Descriptive analysis, analysis of variance	Constant	Certainty	[19]
Ukraine Banks	System dynamics modeling	Dynamic	Uncertainty	[20]

3. METHODOLOGY

This section presents the approach used to model credit risk in Kenya. The case study and variables are first presented, and the main aspects of the data collection and model building are explained in detail throughout the rest of this section.

3.1. Study Data and Variables

Document analysis and focus-group discussions (FGDs) were the primary techniques of data gathering in this study. For validity and reliability, ten semi-structured interview schedules were administered to various staff members who perform core functions of credit risk analysis in a pilot test. The same interview schedules were then re-administered to the same respondents after two weeks and the results obtained were verified for accuracy and correctness. In order to analyze the qualitative data collected, a thematic approach was used. These themes included general and technical knowledge about causes of customer default. A set of nine variables were considered for the study, i.e., customer personal characteristics, customer income, creditor characteristics, issued loans, performing loans, non-performing loans, application scoring, inquired funds, and collateral amount.

A sample size of 29 respondents from the different categories of financial institutions shown in Table 2 was drawn from a population of 203 entities, i.e., 200 financial institutions and 3 CRBs. The respondents were staff members involved in core credit-related functions and formed the sample size *n* a advised by Nasiurma's model [25]:

$$n = \{Ncv^2)/[cv^2 + (N-1)e^2] \quad (1)$$

where *N* is the population, *cv* is coefficient of variation taken to be (0.5) and *e* is tolerance level at 95% confidence level (0.05). This is 14% of the entire population of financial institutions and CRBs. Table 2 shows the study population and sample.

Table 2. Sample size selected from CRBs and financial institutions

Group	Target population	Sample size	Sample size as % of population
Licensed CRBs	3	1	33%
Tier 1 Commercial banks	5	1	20%
Tier 2 Commercial banks	14	3	21%
Tier 3 Commercial banks	17	4	24%
Licensed SACCOs	164	20	12%
Total	203	29	14%

3.2. Implementation Procedure

The first meeting was made with study participants to brief them on the research to be undertaken and to introduce them to the system dynamics modelling approach. Representatives from each of the groups listed in Table 2 attended and gave their informed consent. The second meeting was to discuss the factors influencing non-performance of loans; credit defaulting and current credit rating measures in a recorded focus-group setting. Loosely structured discussions of various topics of interest were administered to respondents in 5 focus groups. Since FGDs were structured, directed and expressive, they yielded a lot of information in a relatively short time. A summary of number of questions given to each focus group are summarized in Table 3.

Table 3. Focus groups response rate.

Focus Group	Items Discussed	No. of Questions (%)	No. of Participants
1	Customer personal characteristics and customer income	25%	6
2	Creditor characteristics	12.5%	5
3	Issued loans, performing loans non-performing loans	25%	6
4	Application scoring	18.5%	6
5	Inquired funds and collateral amount	18.75%	6
		100%	29

Responses from the participants, most of whom are experts in credit risk modeling, formed the disaggregated data that were used for parameter estimation. The third visit entailed a presentation using Vensim software for developing causal loop diagrams and stock-and-flow diagrams to confirm that everything discussed has been properly presented and accurately recorded. For a comprehensive background on the modelling and applications using system dynamics, See Sterman's seminal book [21].

4. RESULTS

This section presents the approach used to model credit risk in Kenya. The case study and variables are first presented, and the main aspects of the data collection and model building are explained in detail throughout the rest of this section.

4.1. Focus Group Discussions

Out of the 29 participants, 18 (i.e., 62%) were male while 11 (i.e., 38%) were female. In terms of profession, participants comprised six asset managers, six financial risk managers, one business analyst, two internal auditors, five credit analysts and nine loan officers. A summary of number of questions given to each FG, which were 100% responded to, are summarized in Table 3.

All the respondents agreed that female applicants posed less credit risk than their male counterparts, and that loan applicants who were married had less capability for defaulting on their loans than their single counterparts. Generally, the study participants agreed that issues such as employment details (including contract expiry), gross and net monthly salary, mobile banking details and monthly financial commitments come into play when determining credit risk. Participants were also synonymous in agreement that sometimes creditors can decide to forgo the investment of loan. For instance, a mortgage applicant with a superior credit rating and a stable income was likely to be seen as posing a lower credit risk and was likely to get a low interest rate on mortgage.

The amount of loan issues, as well as the number of active loans were found to largely determine a borrower's ability to pay. The number and quantity of performing and non-performing loans by both the creditor and the borrower were also brought up as major risk determinants for banks and microfinance institutions. All other factors held constant, the amount of funds inquired by an individual or business was positively associated with the borrower's ability to repay and, thus, also positively associated to the credit risk for the issuing bank or microfinance institution.

4.2. System Dynamics Model

The variables and sub-variables identified from the FDs and the disaggregated baseline data that were provided by participants formed the basis for developing the credit risk architecture presented in Figure 1. A feedback loop forms when the feedback returns back to the originating variable, resulting in a closed loop. An example is the loop between the variables *performing loans → customer income → expenditure → marital status → repayment ability → performing loans*. Such loops are important for determining the general behavior of the system.

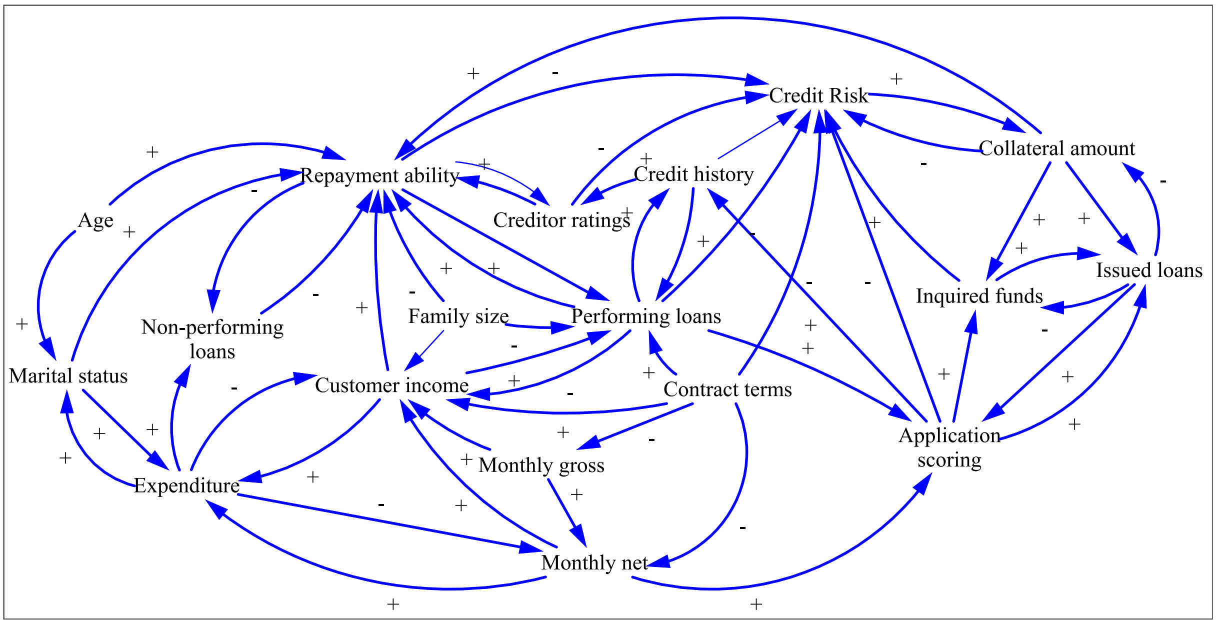

Figure 1. A causal loop diagram of credit risk for banks and microfinance institutions in Kenya

A loop with an even number of negative links is a growth-producing, often destabilizing loop, while one with an odd number of negative loops – such as the one referred to above – indicates a balancing loop. It is usually preferred that the dominant loop is a balancing one, which is not the case with the study model depicted above.

4.3. Simulation of Credit Risk Management

All the variables from the causal loop diagram were retained and a quantitative model was constructed as shown in Figure 2 to run the simulation.

The variables *Monthly Net*, *Customer Income*, *Loan Repayment*, *Expenditure*, *Credit Risk* and *Performing Loans* are stock variables. This means that they contain a quantity which can increase or decrease depending on the amount flowing into or out of the variables. Other variables such as *monthly remittance* are flow variables. This means that monthly remittance controls the number of units (i.e., Kenya Shillings) that flow from the variable Customer income to the variable Loan repayment. Other variables such as *contract terms*, *credit history* and *collateral amount* simply inform the model.

4.4. Sensitivity Analysis

The third objective was to validate the developed model. This was done through sensitivity analysis of variables and comparing the results with what can be expected. Important variables that were identified for the model were *Loan repayment*, *performing loans*, *credit risk*. Whenever changes were made to other variables in the model, these 3 variables were heavily influenced. Therefore, the testing and validation of the model concentrated on sensitivity analysis while observing these variables over an observation period of 5 years (60 months). For the sensitivity analysis the values of all output variables (*Loan repayment, performing loans* and *Credit risk*) were normalized to range from 0-10 to increase consistency in plotting and visualization.

Figure 3 shows the results of sensitivity analysis conducted on the model as part of the validation test by adjusting the borrower's expenditure from Kes 50,000.00 to 75,000.00 per month. The results show that with 50% increase in monthly expenditure, the performing loans dropped from an index of 8.9 out of 10 to 5 out of 10 by month 33 of observation, and further to 2.5 out 10 by month 60 of observation. At the same time the loan repayment which had been stable over several months dropped drastically between month 30 and 60 by which time it had moved from 8.9 out of 10 to 1.7 out of 10. Consistent with the two observations, credit risk increased systematically with the increase in borrower's expenditure, following an S-shaped pattern of behavior. Starting from month it rose sharply and continued to rise until the end of the observation period by which it was at 8.45 out of 10.

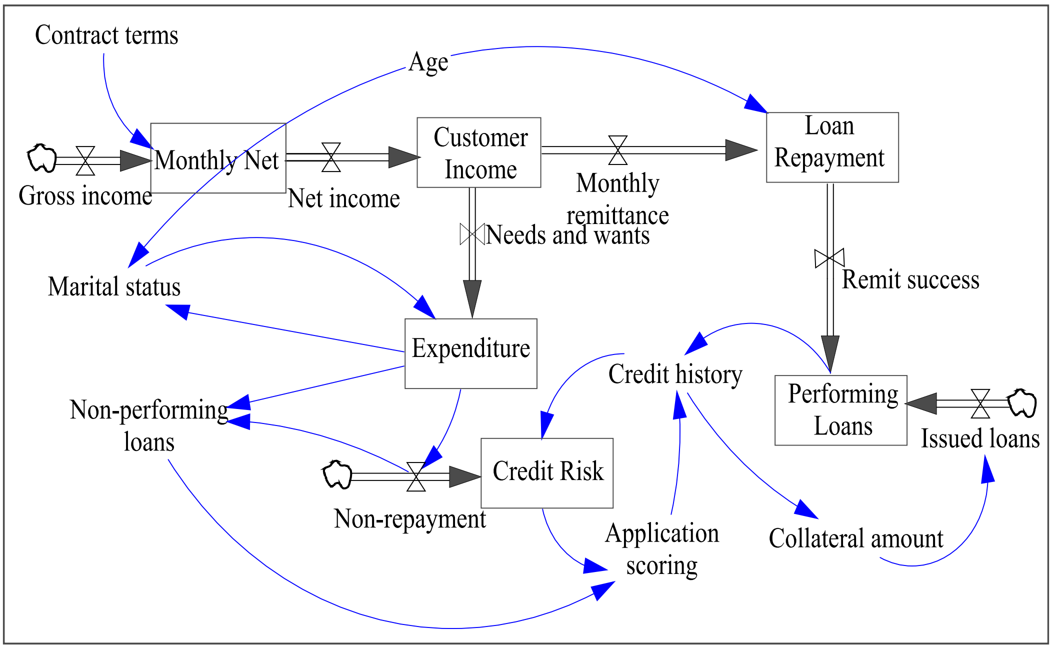

Figure 2. Quantitative Stock-and-flow model of credit risk for banks and microfinance institutions in Kenya

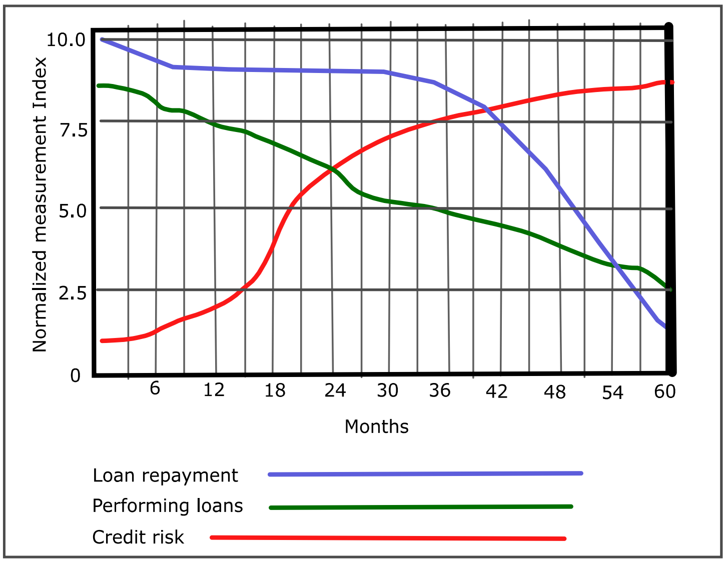

Figure 3. Quantitative Stock-and-flow model of credit risk for banks and microfinance institutions in Kenya

4. DISCUSSION AND CONCLUSION

The objectives of this study were to determine the factors that influence credit risk and to develop a system dynamics model for determining credit. Three main factors were prominent from the observations as well as the sensitivity analysis that was conducted. These were the loan repayment ability, the number of performing loans, and credit risk. These three variables were mostly influenced by factors such as the borrower's income and expenditure and the loan remittance amount. The findings of this study are consistent with the findings of past studies [26-30]. For instance, Duong and Huong concluded after conducting a credit risk analysis of Vietnamese banks in 2017 that borrowers' income significantly affected their ability to pay loans, which in turn contributed to credit risk as has also been seen in this study [26]. Several other researchers found out that social and economic aspects of borrowers were major determinants of credit risk [27, 28]. While both studies concluded that there can be no certainty of optimal outcomes, an increase in the borrower's income and a decrease in other primary and secondary expenditures will both improve credit risk.

In a series of local studies done on credit risk in Kenya, the researchers concluded that considering the high number of loan defaults per year, measures must be taken by financial institutions to rigorously assess their potential borrowers, but in the case of unexpected outcomes then the financial institutions should consider mitigations such as renegotiating the repayment amount [29,30]. This is consistent with what the current study observed, because when the repayment amount was reduced, the credit risk reduced significantly. This means that there is a positive correlation between reduction in loan remittance amount and the ability for borrowers to repay their loans.

Although the current study had many important findings, it was also faced by several limitations. The first limitation is that the current research did not consider the influence of the country's variation in the gross domestic product (GDP) even though a country's economy largely affects how individuals and businesses sustain their income or repay their loans. Additionally, the study did not take account of the direct factors resulting from measures imposed by the government to curb the COVID-19 pandemic, and how these measured affected business operations.

Regarding the stability of the system dynamics model, the limitation encountered was that the variables applied were constructed using data from limited sources, i.e., FGDs and credit default statistics. The research did not use raw data from financial institutions or conduct a countrywide survey of borrowers. The model was also restricted to a few variables, which limited its predictive capability.

The findings in this study indicate that when the income of borrowers decreases or their expenditure increase, as has mostly been witnessed during the recent pandemic period this can significantly decrease their ability to repay loans, and in turn increase credit risk for banks and microfinance institutions. For effective economic assessment, a careful analysis is needed to determine the extent to which this income-expenditure balance is affecting credit risk across all financial institutions countrywide. Optimal determination of credit risk also needs to consider other factors in the ecosystem such as socioeconomic, political and environmental influences. study recommends as policy actions, that the existing models of credit risk management used in the financial sector should be scaled up to incorporate research outcomes. The upgrading of credit evaluation systems is necessary to address the numerous financial-related issues that crop up when borrowers fail to repay loans and lead to heavy losses for the issuing lending institutions, which in turn affects the country's economy. Incorporation of recent research outcomes into the revamping of current credit risk management models will go a long way to significantly reduce the possibility of credit risk and insolvency of commercial banks and microfinance institutions in Kenya.

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REFERENCES

[1] BCBS. *Principles for the Management of Credit Risk*. Consultative paper, The Basel Committee on Banking Supervision, 2001.
[2] CBK. *Bank Supervision Annual Report*. Available at https://www.centralbank.go.ke/uploads/399346751_2015%20Annual%20Report.pdf, 2015.
[3] CBK. *Bank Supervision Annual Report*. Available at https://www.centralbank.go.ke/uploads/banking_sector_annual_reports/1174296311_2018%20Annual%20Report.pdf, 2018.
[4] Kansiime, MK, Tambo, JA, Mugambi, I, Bundi, M, Kara, A, Owuor, C. COVID-19 implications on household income and food security in Kenya and Uganda: Findings from a rapid assessment. *World development*. 2021, p. 137, 105199.
[5] Akkoc, S. An empirical comparison of conventional techniques, neural networks and the three stage hybrid adaptive neuro fuzzy inference system (ANFIS) model for credit scoring analysis: the case of Turkish credit card data. *European Journal of Operational Research* 2012; 222: 168-178.
[6] Moradi, S, Rafiei, FM. A dynamic credit risk assessment model with data mining techniques: evidence from Iranian banks. *Financial Innovation* 2019; 5(1): 1-27.
[7] Munene, RN, Nyamache, T, Nzioki, PM. An Assessment of the Role of Credit Reference Bureau in Influencing Risk Identification in Mitigating Credit Default in Commercial Banks in Kenya, 2018.
[8] Brown, M, Jappelli, T, Pagano, M., Information sharing and credit: Firm-level evidence from transition countries. *Journal of Financial Intermediation* 2009; 18(2): 151-172.
[9] Emel, A, Oral, M, Reisman, A, Yolalan, R. A credit scoring approach for the commercial banking sector. *Socio-Economic Planning Sciences* 2003; 37(2): 103-123.
[10] Kruppa, J, Schwarz, AG, & Ziegler, A. Customer credit risk: individual probability estimates using machine learning. *Expert Systems with Applications* 2013; 40(13): 5125-5131.
[11] Yu, L, Wang, S, Lai, KK, Zhou, L. *BioInspired Credit Risk Analysis*. Berlin, GERMANY: Springer, 2008.
[12] Zanin, M, Papo, D, Sousa, P. A, Menasalvas, E, Nicchi, A, Kubik, E, Boccaletti, S. Combining complex networks and data mining: why and how. *Physics Reports* 2016; 635: 1-44.
[13] Rahim, FHA, Hawari, NN, Abidin, NZ. Supply and demand of rice in Malaysia: A system dynamics approach. *International Journal of Supply Chain and Management* 2017; 6(4): 234-240

[14] Afriyie, HO, Akotey, JO. Credit risk management and profitability of selected rural banks in Ghana. *Catholic University College of Ghana*, vol. 7(4), 2012, pp. 176-181.

[15] Onaolapo, AR. Analysis of credit risk management efficiency in Nigeria commercial banking sector, (2004-2009). *Far East Journal of Marketing and Management* 2012; 2(4): 39-52.

[16] Abdipoor, S, Nasseri, A, Akbarpour, M, Parsian, D, Zamani, S. Integrating neural network and colonial competitive algorithm: a new approach for predicting bankruptcy in Tehran security exchange. *Asian Economic and Financial Review* 2013; 3(11): 1528-1539.

[17] Maji, SG, Hazarika, P. Factors affecting credit risk of Indian banks: Application of dynamic panel data model. *Research Bulletin* 2016; 42(1): 85-96.

[18] Otieno, S, Nyagol, M, Onditi, A. Relationship between credit risk management and financial performance. Empirical evidence from microfinance banks in Kenya. *Research Journal of Finance and Accounting* 2016; 7(6): 2222-2847.

[19] Kithinji, AM. Credit risk management and profitability of commercial banks in Kenya. *School of Business*, Nairobi, KENYA: University of Nairobi, 2010.

[20] Kaminskyi, A. *System Dynamics Modelling of Credit Risk Management*. 2018.

[21] Sterman, DJ. *Business Dynamics: Systems Thinking for a Complex World*. Boston, Mass. USA: Irwin/ McGraw-Hill, 2000.

[22] Reuter, J. Values and Worldviews. *Diagnosing and Engaging with Complex Environmental Problems*. 2013, pp. 62-64.

[23] Csikosova, A, Janoskova, M, Culkova, K. Limitation of financial health prediction in companies from post-communist countries. *Journal of Risk and Financial Management* 2019; 12: 13-15.

[24] Petrică, AC, Stancu, S, Tindeche, A. Limitation of ARIMA models in financial and monetary economics. *Theoretical & Applied Economics* 2016 23(4).

[25] Nasiurma, D. K. *Survey Sampling: Theory and methods*. 2010. Nairobi, Kenya. University of Nairobi.

[26] Duong, NT, Huong, TTT. The analysis of major credit risk factors-The case of the Vietnamese commercial banks. *International Journal of Financial Research* 2017; 8: 33-42.

[27] Belás, J, Smrcka, L, Gavurova, B, Dvorsky, J. The impact of social and economic factors in the credit risk management of SME. *Technological and Economic Development of Economy* 2018; 24(3): 1215-1230.

[28] Frei, C. A New Approach to Risk Attribution and Its Application in Credit Risk Analysis. *Risks* 2020; 8(2): 60-65.

[29] Ngumo, KOS, Collins, KW. David, SH., Determinants of financial performance of microfinance banks in Kenya. *arXiv preprint arXiv*:2010.12569, 2020.

[30] Misati, RN, Kamau, A, Tiriongo, S, Were, M. Credit risk and private sector loan growth under interest rate controls in Kenya. *African Review of Economics and Finance* 2021; 13: 83-112.