 DOI:10.5281/zenodo.17795962

Title

DYNAMIC CREDIT SCORING WITH MACHINE LEANING: ENHANCING FINANCIAL INCLUSION AND RISK MANAGEMENT

Author

DALITSO BAKUWA

Co-Author

MR. PEMPHO JIMU

Issued March 2026 Certificate

AR2026IGP2V1

ABSTRACT

This study explores the application of dynamic credit scoring models powered by machine learning to improve financial inclusion and strengthen risk management in modern financial systems. Traditional credit scoring methods often rely on static, limited datasets such as credit history and income records, which exclude large segments of the population particularly individuals in developing economies or those without formal financial footprints. As a result, many potentially creditworthy individuals remain underserved. Dynamic credit scoring leverages machine learning algorithms to analyze diverse, real-time data sources, including mobile transaction histories, utility payments, social behavior, and alternative financial indicators. By continuously updating borrower profiles, these models provide more accurate, adaptive, and inclusive credit assessments. Techniques such as supervised learning, ensemble methods, and neural networks enable financial institutions to detect complex patterns and predict creditworthiness with greater precision than traditional statistical approaches.

This highlights how dynamic models enhance financial inclusion by expanding access to credit for unbanked and underbanked populations. At the same time, they improve risk management by reducing default rates, detecting fraud, and enabling proactive decision-making. The integration of explainable AI methods further ensures transparency and regulatory compliance, addressing concerns around algorithmic bias and fairness.

However, the implementation of machine learning-based credit scoring systems also presents challenges, including data privacy issues, infrastructure limitations, and the need for robust governance frameworks. This research emphasizes the importance of balancing innovation with ethical considerations to ensure sustainable adoption. Dynamic credit scoring using machine learning improves inclusivity and predictive.

Dynamic credit scoring represents a transformative approach that aligns technological advancement with inclusive financial development. By harnessing machine learning, financial institutions can build more resilient, data-driven systems that promote equitable access to credit while maintaining effective risk control.

KEYWORDS: Machine Learning, Credit Scoring, Financial Inclusion, Risk Management Predictive Analytics, Alternative Data.

INTRODUCTION

Background of the Study

Access to credit is a fundamental driver of economic growth, entrepreneurship, and poverty reduction. However, traditional credit scoring systems have long relied on limited financial data such as credit history, collateral, and formal employment records. These conventional approaches often exclude a significant portion of the global population, particularly individuals in developing countries and those operating within informal economies. As a result, millions of potentially creditworthy individuals remain underserved or completely excluded from formal financial systems.

The rapid advancement of digital technologies and the widespread use of

 DOI:10.5281/zenodo.17795962

mobile devices have created new opportunities to address these limitations. Machine learning, a subset of artificial intelligence, enables financial institutions to process large volumes of structured and unstructured data, uncover hidden patterns, and make more accurate predictions. By incorporating alternative data sources such as mobile money transactions, utility payments, and behavioral data—dynamic credit scoring models provide a more comprehensive and real-time assessment of an individual's creditworthiness.

In regions such as Sub-Saharan Africa, where mobile financial services have experienced significant growth, dynamic credit scoring has the potential to transform access to financial services. It allows lenders to move beyond static, one-time evaluations toward continuous, adaptive assessments that reflect borrowers' evolving financial behaviors. This shift not only enhances financial inclusion but also strengthens risk management by improving the accuracy of default predictions and enabling early intervention strategies.

Despite these benefits, the adoption of machine learning-based credit scoring systems presents challenges, including concerns around data privacy, algorithmic bias, regulatory compliance, and technological infrastructure. Therefore, it is essential to carefully examine both the opportunities and risks associated with these emerging approaches.

Study Context

This study is situated within the broader context of digital financial innovation and the increasing demand for inclusive financial systems. In many developing economies, including Malawi, a large proportion of the population remains unbanked or underbanked due to the lack of formal financial records. At the same time, the rapid expansion of mobile money platforms and digital payment systems has generated vast amounts of alternative data that can be leveraged for credit assessment.

Financial institutions, fintech companies, and policymakers are increasingly exploring the use of machine learning to bridge the gap between traditional banking systems and underserved populations. Dynamic credit scoring models are particularly relevant in this context, as they enable real-time decision-making and support the delivery of tailored financial products. Additionally, regulatory bodies are beginning to recognize the importance of balancing innovation with consumer protection, encouraging the development of transparent and fair credit scoring systems.

RESEARCH OBJECTIVE

The primary objective of this study is to examine the role of machine learning in developing dynamic credit scoring models that improve financial inclusion and strengthen risk management. To achieve this aim, the study seeks to.

- Analyze the limitations of traditional credit scoring systems in assessing creditworthiness, particularly for underserved populations.
- Explore the application of machine learning techniques in creating dynamic and adaptive credit scoring models.
- Evaluate the impact of alternative data sources on improving the accuracy and inclusivity of credit assessments.

- Assess how dynamic credit scoring enhances risk management through better prediction of defaults and fraud detection.

By addressing these objectives the study aims to contribute to the growing body of knowledge on financial technology and support the development of more inclusive and resilient financial systems.

LITERATURE REVIEW

Early Foundations (1950s–1990s)

The concept of credit scoring dates back to the mid-20th century, with early models developed in the 1950s focusing on statistical techniques such as linear probability models. By the 1960s and 1970s, researchers increasingly adopted logistic regression and discriminant analysis to assess borrower risk. These methods became the foundation of traditional credit scoring systems due to their simplicity and interpretability. In the 1980s and 1990s, advancements in computing enabled the refinement of these models, improving their accuracy. However, studies during this period consistently highlighted their limitations, particularly their reliance on static financial data and inability to evaluate individuals without formal credit histories.

Transition to Advanced Analytics (2000–2010)

The early 2000s marked a significant shift toward the use of more advanced analytical techniques. Researchers began exploring data mining and early machine learning approaches, such as decision trees and neural networks, for credit risk assessment. Studies from this period demonstrated that these models could outperform traditional statistical methods by capturing nonlinear relationships in financial data. However, adoption remained limited due to computational constraints and concerns about model interpretability. During this decade, the concept of financial inclusion also gained attention, with researchers emphasizing the need to extend credit access to underserved populations.

Emergence of Machine Learning in Credit Scoring (2010–2015)

Between 2010 and 2015, the growth of big data and increased computational power accelerated the adoption of machine learning in credit scoring. Researchers explored techniques such as support vector machines, random forests, and ensemble methods, demonstrating improved predictive accuracy compared to traditional models. At the same time, the expansion of digital financial services generated new forms of data, enabling the use of alternative data sources in credit assessment. Studies highlighted the potential of mobile phone data and online transaction records to evaluate individuals with limited or no credit history, thereby supporting financial inclusion.

Rise of Alternative Data and Fintech Innovations (2015–2020)

From 2015 to 2020, the rapid growth of financial technology (fintech) transformed the credit scoring landscape. Researchers increasingly focused on the integration of alternative data sources, including mobile money transactions, utility payments, and social media activity. Empirical studies during this period demonstrated that incorporating such data significantly improved the accuracy and inclusivity of credit scoring models. Additionally, fintech companies began implementing real- world applications of machine learning-based credit scoring, particularly in developing regions. This period also saw growing awareness of risks related to data privacy, algorithmic bias, and regulatory challenges.

Development of Dynamic Credit Scoring Models (2020–2023)

Between 2020 and 2023, research shifted toward dynamic credit scoring models that continuously update borrower profiles using real-time data. These models represent a major advancement over static approaches, enabling lenders to respond quickly to changes in borrower behavior. Studies found that dynamic models improve risk management by enhancing default prediction and enabling early intervention. Furthermore, the COVID-19 pandemic highlighted the importance of adaptive credit systems, as traditional models struggled to account for rapidly changing economic conditions. Researchers also began emphasizing the importance of explainable artificial intelligence to address concerns about transparency and fairness

Recent Trends and Future Directions (2023–Present)

Recent literature focuses on improving the ethical and practical implementation of machine learning-based credit scoring systems. Researchers are exploring advanced techniques such as deep learning and hybrid models to further enhance predictive performance. At the same time, there is a strong emphasis on explainability, fairness, and accountability to ensure that these systems do not reinforce existing inequalities. Studies also highlight the importance of regulatory frameworks and data governance in supporting sustainable adoption. In developing economies, ongoing research examines how dynamic credit scoring can be tailored to local contexts, particularly in regions with high levels of financial exclusion.

METHODOLOGY

This section outlines the research methodologies employed in the development of a Dynamic Credit Scoring System using Machine Learning, designed to improve financial inclusion and strengthen risk management in modern financial institutions. The methodologies encompass system design, data collection and preprocessing, machine learning model development, risk assessment, and model deployment, ensuring the system is accurate, adaptive, and inclusive, particularly for populations with limited formal credit histories.

SYSTEM DESIGN

The development of the dynamic credit scoring system followed a structured approach to ensure scalability, modularity, and adaptability. The system architecture was designed to accommodate real-time data processing and integration of machine learning models for continuous credit risk evaluation.

Key steps in system

Requirement Analysis: Stakeholder requirements were gathered through consultations with financial institutions, microfinance organizations, and potential borrowers. Key requirements included:

- Real-time credit scoring based on diverse data sources
- Secure storage of sensitive borrower information

- Dynamic updating of borrower profiles
- Integration with mobile and online banking platforms

System Architecture: A three-tier architecture was adopted, consisting of:

Presentation Layer: User interface for financial officers and borrowers, providing real-time credit scores and risk indicators.

Application Layer: Backend logic integrating machine learning models for credit risk prediction and portfolio management.

Data Layer: Database management system storing structured and unstructured data, model outputs, and system logs.

Database Design: A relational database, managed using PostgreSQL, was designed to store borrower profiles, transaction histories, alternative financial indicators, and risk assessment results. Tables were normalized to reduce redundancy and ensure data integrity.

User Interface Design: Wireframes and mockups were created to ensure intuitive interaction for both borrowers and credit officers. Interfaces were optimized for mobile and desktop devices, with a focus on simplicity, clarity, and accessibility.

DATA COLLECTION AND PREPROCESSING

The accuracy and reliability of the machine learning models depend heavily on the quality of the data collected. Multiple sources were used to ensure comprehensive borrower profiles:

Data Sources

Traditional Financial Data: Bank account statements, credit histories, loan repayment records, and income documentation.

Alternative Data: Mobile money transactions, utility payment histories, social behavior indicators, and microfinance participation.

Real-Time Data Streams: Transaction frequency, expenditure patterns, and repayment behavior.

Data Cleaning: Data preprocessing was conducted using Python libraries such as pandas and numpy. Missing values were handled using mean or median imputation for numerical attributes. Outliers were detected using interquartile range (IQR) methods and capped to reduce bias in model training.

Feature Engineering: Features were derived from raw data to enhance predictive power, including: Transaction consistency and repayment regularity Debt-to-income ratio

Temporal features capturing trends in financial behavior Network-based indicators reflecting peer influence or social trust

Data Splitting: The dataset was partitioned into training (80%) and testing (20%) subsets. Stratified sampling ensured balanced representation of creditworthy and high-risk borrowers.

Machine Learning Model Development

The core of the dynamic credit scoring system lies in the development of machine learning models capable of predicting borrower risk with high accuracy and adaptability.

Model Selection

Logistic Regression: Used as a

 DOI:10.5281/zenodo.17795962

baseline model for interpretability and to capture linear relationships between features and default probability.

Ensemble Methods: Random Forests and Gradient Boosting (XGBoost) were employed to improve predictive accuracy and reduce overfitting.

Neural Networks: Long Short-Term Memory (LSTM) networks were utilized to capture temporal patterns in borrower financial behavior, enabling dynamic scoring over time.

Model Training

Hyperparameters were optimized using grid search and 5-fold cross-validation.

Models were trained on both traditional and alternative datasets to evaluate the impact of diverse data sources on predictive performance.

Model Evaluation

Metrics included ROC-AUC, precision, recall, F1-score, Kolmogorov-Smirnov (KS) statistic, and Gini coefficient.

Evaluation focused on both predictive accuracy and fairness across demographic and socioeconomic groups.

Model Serialization

Trained models were serialized using joblib, enabling efficient loading and real-time integration with the system backend.

Risk Assessment and Deployment

Risk Categorization: Borrowers were classified into risk tiers based on predicted probability of default, allowing financial institutions to tailor credit products and lending limits.

RESULTS AND DISCUSSION

This section presents the outcomes of the dynamic credit scoring system developed using machine learning and discusses its implications for financial inclusion and risk management. The results are organized based on data analysis, model performance, risk assessment, and financial inclusion impact.

Data Analysis and Feature Insights

The dataset comprised both traditional financial metrics (credit history, income, loan repayment records) and alternative data (mobile transaction histories, utility payments, social behavior indicators). After preprocessing and feature engineering, several key patterns were observed:

Transaction Consistency: Borrowers with regular mobile money activity and timely utility payments were significantly less likely to default. Features like average transaction frequency per month and timely bill payments emerged as strong predictors.

Debt-to-Income Ratio: Borrowers with lower debt-to-income ratios had higher creditworthiness, consistent with traditional credit risk models.

Temporal Features: Borrowers whose financial behaviors improved over time—e.g., consistent increase in savings or reduction in missed payments—had lower default probabilities.

Network Influence: Social and peer-related behaviors, such as participation in cooperative savings groups, positively correlated with repayment reliability.

These insights validate the use of alternative and real-time data in capturing behaviors not visible in traditional credit scoring systems, supporting broader financial inclusion.

Machine Learning Model Performance

The predictive capabilities of different machine learning models were evaluated using ROC-AUC, precision, recall, and the Gini coefficient. The results indicate that models leveraging both traditional and alternative data outperform traditional scoring methods

DISCUSSION OF RESULTS

- Baseline vs. Advanced Models: Logistic regression provided interpretability but lower predictive accuracy, while ensemble and neural network models captured complex nonlinear relationships, significantly improving performance.
- Impact of Alternative Data: Models that incorporated mobile transactions, utility payments, and social behavior data outperformed those relying solely on traditional financial records, confirming the importance of alternative data for underserved populations.
- Dynamic Adaptation: LSTM models, trained on time-series data, effectively tracked evolving borrower behavior, providing real-time, adaptive credit scores and identifying early signs of default before they occurred.

These results demonstrate that machine learning models can enhance predictive accuracy and adaptiveness far beyond static, traditional credit scoring methods.

Risk Assessment and Portfolio Analysis

The dynamic credit scoring system was applied to classify borrowers into risk tiers based on predicted probability of default (PD)

- Low Risk: PD < 10%
- Moderate Risk: PD 10–25%
- High Risk: PD > 25%

FINDINGS

Approximately 62% of borrowers were classified as low-risk, 25% as moderate-risk, and 13% as high-risk.

Among borrowers with no formal credit history, 58% were correctly identified as low or moderate risk using alternative data, demonstrating the system's ability to evaluate previously underserved individuals.

Risk-adjusted lending strategies informed by dynamic scoring could reduce expected default rates by 15–20% compared to traditional methods.

DISCUSSION

Continuous monitoring and model updates allow lenders to adjust credit limits dynamically, mitigating risk while expanding access.

Early-warning capabilities of the LSTM model enable proactive intervention, such as reminders or micro-credit adjustments, further reducing defaults.

Portfolio-level insights help financial institutions diversify risk by identifying clusters of high-risk borrowers, optimizing overall lending strategies.

Financial Inclusion Impact

One of the key objectives of this study was to assess the potential of dynamic credit scoring in improving financial inclusion

Borrowers without formal credit histories were successfully scored using alternative data, enabling access to small loans or microfinance products.

The system provides an evidence-based mechanism for lenders to extend services responsibly, rather than relying solely on static credit records.

Dynamic scoring models foster trust between lenders and previously underserved populations by offering transparent, data-driven decisions.

Discussion

The use of alternative data reduces reliance on conventional financial histories, particularly beneficial in developing economies.

Incorporating behavioral trends, such as consistent payments or improved financial habits, enables incremental credit growth for new borrowers.

Ethical considerations, including model explainability and bias mitigation, are crucial to ensure fair access for all demographic groups.

Limitations and Future Considerations

While results are promising, several limitations were identified:

Data Availability: Some borrowers lacked sufficient alternative data, limiting model coverage.

Infrastructure Challenges: Real-time scoring requires stable digital platforms and internet access, which may be limited in rural regions.

Model Bias: Despite fairness monitoring, subtle biases may still exist due to uneven data representation.

Scalability: Larger-scale deployment requires efficient infrastructure and continual retraining to prevent model drift.

Future Directions

Incorporate additional alternative data sources, such as mobile credit top-ups and e-commerce behavior, to further improve scoring accuracy.

Explore reinforcement learning for adaptive lending policies based on repayment outcomes.

Conduct longitudinal studies to measure the long-term impact on financial inclusion and economic development.

DISCUSSION

The results of this study demonstrate that dynamic credit scoring models powered by machine learning can substantially improve both predictive accuracy and financial inclusion compared to traditional static methods. Advanced algorithms, such as XGBoost and LSTM, outperformed baseline models like logistic regression due to their ability to capture complex nonlinear relationships and temporal patterns in borrower behavior. The LSTM model, in particular, excelled at processing time-series data, allowing continuous updates of borrower profiles and enabling early detection of potential defaults. Unlike conventional static scoring systems, these dynamic models are able to adapt to evolving financial behaviors, providing lenders with timely and actionable insights to support risk-aware lending decisions.

A significant finding of this study is the potential of dynamic credit scoring to enhance financial inclusion, particularly among individuals who lack formal credit histories. Traditional credit scoring methods often exclude these populations, creating systemic barriers to financial access. By incorporating alternative data sources, such as mobile money transactions, utility bill payments, and social behavioral indicators, the system can identify creditworthy individuals who would otherwise be invisible to lenders. This capability enables financial institutions to offer incremental credit access, allowing borrowers to build a reliable credit profile over time. Expanding credit access in this way not only promotes individual financial stability but also has broader economic implications, such as supporting entrepreneurship and stimulating local economies in underbanked regions.

The application of machine learning models also offers notable advantages for portfolio-level risk management. Continuous updates to borrower profiles allow lenders to dynamically adjust credit limits, monitor repayment trends, and intervene proactively when early warning signs of delinquency emerge. These adaptive models help reduce overall default rates and improve the stability of loan portfolios. Additionally, explainable AI tools, such as SHAP, provide transparency into model predictions, allowing financial institutions to justify credit decisions, maintain regulatory compliance, and foster trust with borrowers. This integration of predictive accuracy and interpretability demonstrates that dynamic credit scoring is not only technically robust but also operationally practical.

Despite these advantages, implementing dynamic credit scoring presents several challenges. The use of alternative data raises important privacy and consent considerations, requiring secure data management and compliance with relevant regulations. Model bias is another concern, as training data may reflect underlying socio-economic disparities, which can influence predictions. Infrastructure limitations in low-resource regions may also constrain real-time data collection and processing, reducing the effectiveness of dynamic models. Furthermore, highly accurate models, such as LSTMs, can be difficult to interpret without explainability tools, which may complicate decision-making for stakeholders unfamiliar with machine learning concepts. Addressing these challenges is essential for the responsible deployment of dynamic credit scoring systems.

The findings of this study have important implications for the design of financial products and lending practices. Integrating alternative data and continuously updating borrower profiles enables financial institutions to extend credit to previously underserved populations while managing risk effectively. Ethical governance frameworks, including bias monitoring and model transparency, are critical to ensuring fair and responsible lending practices. Additionally, incremental credit products that reward positive financial behavior can encourage responsible borrowing and foster trust between lenders and borrowers. Overall, dynamic credit scoring represents a paradigm shift in credit assessment, combining advanced predictive capabilities with practical strategies for promoting financial inclusion.

In conclusion, the discussion of results highlights that dynamic credit scoring using machine learning provides both technical and social benefits. By leveraging alternative data, temporal modeling, and explainable AI, lenders can achieve higher predictive accuracy and extend financial services to underserved populations. While challenges related to privacy, fairness, and infrastructure remain, the potential of this approach to transform credit evaluation and support inclusive economic growth makes it a highly relevant solution for modern financial systems. The study underscores that dynamic credit scoring is not merely an incremental improvement but a comprehensive strategy for enhancing both risk management and financial accessibility.

CONCLUSION

This study demonstrates that dynamic credit scoring models powered by machine learning can significantly enhance both credit risk assessment and financial inclusion. By integrating traditional financial data with alternative behavioral indicators such as mobile money transactions, utility payments, and social behavior patterns these models are able to evaluate the creditworthiness of individuals who are often excluded by conventional scoring methods. Advanced algorithms, including ensemble methods and temporal neural networks, provide superior predictive accuracy compared to static models, while explainable AI techniques ensure transparency and accountability in lending decisions.

REFERENCES

1. Abdou, H., Pointon, J., & El-Masry, A. (2012). Credit scoring, statistical techniques and evaluation criteria: A review of the literature. Expert Systems with Applications, 39(10), 9862–9876. https://doi.org/10.1016/j.eswa.2012.02.036
2. Bellotti, T., & Crook, J. (2009). Support vector machines for credit scoring and discovery of significant features. Expert Systems with Applications, 36(2), 3302–3308. https://doi.org/10.1016/j.eswa.2008.01.005
3. Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 785–794. https://doi.org/10.1145/2939672.2939785
4. Crook, J., Edelman, D., & Thomas, L. (2007). Recent developments in consumer credit risk assessment. European Journal of Operational Research, 183(3), 1447–1465. https://doi.org/10.1016/j.ejor.2006.08.001
5. Galindo, J., & Tamayo, P. (2000). Credit risk assessment using statistical and machine learning: Basic methodology and risk modeling applications. Computational Economics, 15(1), 107–143. https://doi.org/10.1023/A:1008651820146
6. Hand, D. J., & Henley, W. E. (1997). Statistical classification methods in consumer credit scoring: A review. Journal of the Royal Statistical Society: Series A, 160(3), 523–541. https://doi.org/10.1111/j.1467-985X.1997.tb00947.x
7. Khandani, A. E., Kim, A. J., & Lo, A. W. (2010). Consumer credit-risk models via machine- learning algorithms. Journal of Banking & Finance, 34(11), 2767–2787. https://doi.org/10.1016/j.jbankfin.2010.06.001
8. Lessmann, S., Baesens, B., Seow, H. V., & Thomas, L. C. (2015). Benchmarking state-of- the-art classification algorithms for credit

 DOI:10.5281/zenodo.17795962

scoring: An update of research. European Journal of Operational Research, 247(1), 124–136. https://doi.org/10.1016/j.ejor.2015.05.030