IOSR Journal Of Economics and Finance (IOSR-JEF)
e-ISSN: 2321-5933, p-ISSN: 2321-5925.Volume 17, Issue 1 Ser. 3 (Jan. – Feb. 2026), PP 49-62
www.Iosrjournals.Org

Bridging The Financial Divide: AI-Driven Credit Scoring Models For Underserved Populations

Author

Abstract
Artificial intelligence (AI) has redefined the global credit environment by enhancing the accuracy, inclusivity, and efficiency of lending decisions. This paper critically examines the evolution, architecture, and ethical dimensions of AI-driven credit scoring systems, emphasizing their potential to advance financial inclusion while addressing inherent risks of bias, opacity, and regulatory misalignment. Through an analytical synthesis of recent empirical studies and industry frameworks, this study contrasts traditional credit assessment models which are rooted in static, rule-based approaches, with modern machine learning architectures capable of integrating dynamic, alternative data from mobile money, social transactions, and behavioral patterns. The findings reveal that ensemble learning, neural networks, and hybrid models significantly outperform conventional techniques in predictive accuracy and adaptability, yet persistent challenges remain around explainability, algorithmic fairness, and data governance. Building on comparative analyses, the paper proposes a conceptual framework for inclusive and ethical AI credit scoring, integrating fairness metrics, real-time data pipelines, and bias correction mechanisms to balance performance with accountability. The discussion extends to policy and strategic implications for regulators, fintech innovators, and development agencies, calling for harmonized governance models that align technological innovation with social equity. Lastly, the study argues that the sustainable future of credit access does not only depend on algorithmic sophistication but also on transparent, human-centered systems that embed trust, fairness, and accountability within financial decision-making processes.

Keywords And Phrases: *Artificial Intelligence, Credit Scoring, Financial Inclusion, Explainable AI, Algorithmic Fairness, Responsible Innovation, Governance, Fintech Ethics*

Date of Submission: 18-01-2026 Date of Acceptance: 28-01-2026

I. Introduction

Access to credit is a vital gateway to economic opportunity, enabling entrepreneurship, financial stability, and inclusive growth (Idroes et al., 2024). Yet for millions of individuals and families across the world, particularly in the United States credit access remains limited or entirely out of reach, constraining their ability to pursue sustainable livelihoods and financial advancement.

According to the World Bank, the expansion of digital financial services has reduced the global number of unbanked adults from 2.5 billion in 2011 to 1.4 billion in 2021, with 76 percent of the world's adult population owning a financial account by that year. Despite this progress, persistent disparities between high- and low-income countries highlights the urgent need to advance equitable financial inclusion and ensure fair access to financial services for all (World Bank, 2025).

In the United States, racial and income-based inequities continue to shape the credit landscape. Black and Hispanic households face rejection rates for credit applications that are considerably higher than those of White households, while low-income applicants are often deterred from applying altogether due to anticipated denial (Matteo et al., 2025). Data from the U.S. Census Bureau and the Federal Reserve reveal that these populations consistently report lower credit scores, higher utilization rates, and greater dependence on high-cost financial alternatives (Trevor et al., 2025). This combination of systemic bias and self-exclusion perpetuates unequal credit outcomes and financial vulnerability.

The broader consequence of these disparities is deepened financial exclusion, which widens wealth gaps, restricts upward mobility, and reinforces intergenerational disadvantage. The U.S. Department of the Treasury (2024) reports that in 2022, the median wealth of White families was approximately $285,000, six times greater than that of Black families and five times greater than that of Hispanic families. These patterns highlights that credit access is not merely a financial issue but a cornerstone of social equity and economic justice.

Traditional credit-scoring systems, historically grounded in metrics such as repayment history, credit-account age, and bureau-recorded data, are often misaligned with the financial realities of underserved populations. As Kansas City Fed economist Ying Lei Toh notes, such legacy models can "disproportionately punish consumers from economically disadvantaged groups" because they fail to capture a borrower's true repayment capacity (TEN, 2024). Also, technical challenges, such as class imbalance, verification latency, and concept drift further reduce the predictive validity and fairness of these scorecards (Mokheleli & Museba, 2023). Consequently, many individuals remain "credit invisible" despite demonstrating consistent financial responsibility in other contexts.

Artificial intelligence (AI) is increasingly positioned as a transformative force capable of expanding financial inclusion through alternative data, ranging from mobile-payment records and utility bills to rental histories and social-network behavior (Nuka & Ogunola, 2024). When combined with machine-learning techniques, these broader data sources can more accurately assess creditworthiness and identify individuals who would otherwise be excluded from traditional models. Studies show that integrating call-detail records and social-network analytics alongside conventional credit data improves predictive performance and lowers default risk (Kyeong et al., 2022; Alamsyah et al., 2025). Yet the integration of AI into credit scoring also introduces challenges related to fairness, explainability, and governance, as unmonitored algorithms may replicate or even amplify existing societal biases (Goodness et al., 2025).

The purpose of this paper is to examine how AI-driven credit-scoring models, underpinned by alternative data sources, can help bridge the credit divide affecting unbanked and underbanked populations. Specifically, it evaluates the structural biases embedded in traditional credit systems, conducts a comparative analysis of AI-based credit-scoring frameworks, and proposes a conceptual model that balances predictive accuracy with ethical and transparent AI governance.

The scope of the paper is structured around four core components. The first outlines the nature and scale of financial exclusion and credit-access disparities. The second critiques the limitations of legacy credit-scoring approaches. The third explores the promise and risks of rising AI-based credit frameworks. The fourth presents a conceptual model for deploying AI-driven credit scoring tailored to underserved populations, emphasizing fairness, governance, and ethical safeguards. The paper concludes with strategic recommendations for policymakers, regulators, and financial institutions, alongside directions for future research.

II. The Landscape Of Credit Scoring And Financial Access

Overview of Conventional Credit Scoring Frameworks

Traditional credit-scoring models from FICO, Experian, and Equifax have long shaped consumer credit evaluation by leveraging historical repayment behavior, credit history length, and bureau-reported data. These frameworks, built on large datasets of financially active individuals, use regression and scorecard techniques to categorize borrowers according to their credit risk profiles.

FICO, one of the most influential data analytics firms in consumer finance, provides credit scores used by approximately 95% of major U.S. financial institutions, shaping lending decisions across consumer credit markets (Kagan, 2025). CNBC (2025) reports that there are dozens of FICO score versions, each tailored to the unique risk appetites and assessment needs of lenders, including credit card companies, mortgage providers, and auto financiers. While FICO Score 8 remains the most commonly used general-purpose model, specialized models such as FICO Auto Scores, Bankcard Scores, and the newer FICO Score 10 series are designed for industry-specific applications.

According to Experian (2024), FICO offers a wide spectrum of credit scoring models. Its base scores FICO Score 8, 9, and 10 range from 300 to 850, while industry-specific versions for auto loans and credit cards extend from 250 to 900. In response to the limitations of traditional credit histories, alternative data-based models such as UltraFICO and FICO XD integrate non-traditional data sources, including banking transactions and utility payments. These developments mark an incremental shift toward broader credit inclusion, although adoption remains limited.

Experian (2025) also provides consumers with free access to their FICO® Score and credit report, enabling ongoing credit monitoring and early detection of changes in their credit profile. Equifax, by contrast, offers a proprietary credit score that functions primarily as a consumer-facing tool for personal financial awareness rather than a score used in institutional lending decisions (Arora, 2023). Although this self-assessment framework enhances transparency for individuals, it does not directly influence formal credit eligibility outcomes.

However, recent research emphasizes the structural limitations of these legacy frameworks, especially when applied to non-traditional or underserved populations. As noted by TEN (2024), "legacy credit systems may disproportionately penalize consumers from economically disadvantaged backgrounds" because they fail to recognize alternative behavioral signals of creditworthiness. Borrowers with "thin files"—those lacking robust credit histories or relying primarily on cash and informal economies—are particularly disadvantaged. Fine's (2024) psychometric-based study found that for underbanked consumers, conventional bureau-derived scores often exhibit weak correlations with actual repayment capacity, whereas psychometric metrics improved predictive validity (Gini = 0.28–0.31) when added to traditional scorecards. This finding highlights the potential of behavioral and personality-based data in complementing conventional indicators and advancing financial inclusion.

Kozodoi et al. (2024) further investigate the technical dimensions of bias and sampling limitations within credit-scoring systems, proposing a bias-aware self-learning approach and Bayesian evaluation framework to improve model calibration, particularly in datasets where rejected loan applications create informational blind spots. Through testing on both synthetic and real-world datasets, including randomized controlled trials, the study reports measurable improvements in predictive performance. However, it cautions that while reject inference enhances model robustness, it only modestly mitigates structural bias inherent in legacy credit models. Despite their dominance in U.S. credit systems, traditional models like FICO, Experian, and Equifax fall short for unbanked populations, highlighting the need for AI-driven, inclusive credit assessment tools.

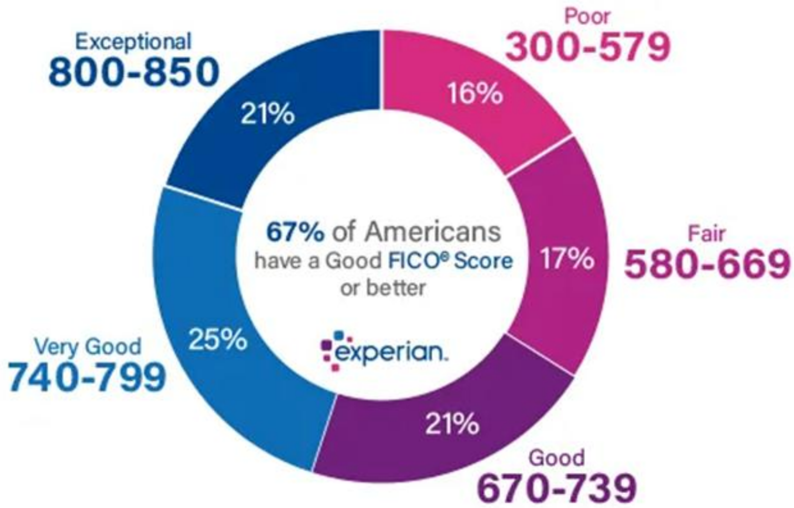

Figure 1: *FICO Scores Ranges*
Source: *Experian report (2024)*

Key Barriers Facing Unbanked and Underbanked Populations

The terms unbanked and underbanked describe groups that remain on the margins of formal finance. Unbanked individuals lack any formal bank account, while underbanked individuals maintain an account but still depend heavily on alternative financial services such as payday lenders, check cashers, or money orders. According to the Federal Deposit Insurance Corporation's (FDIC) 2023 National Survey of Unbanked and Underbanked Households, approximately 5.6 million U.S. households (4.2%) were unbanked and 19 million (14.2%) were underbanked, illustrating the persistence of financial exclusion even in a highly digitized economy (Deichmann, 2025). These groups face multiple systemic and behavioral barriers that inhibit their access to credit and perpetuate inequality.

A major issue is data invisibility, the absence of verifiable financial records that modern credit systems rely upon. Many low-income individuals operate entirely outside the formal financial infrastructure, lacking credit-bureau histories, payroll documentation, or tax records. The Policy and Economic Research Council (PERC, 2025) emphasizes that "Credit Invisibles" are systematically rejected by automated underwriting systems because such models depend on bureau-reported credit data. Without this data, lenders automatically flag these applicants as unscorable, perpetuating a cycle of exclusion and limiting the use of traditional credit-scoring frameworks.

Informal economic participation also deepens this gap. Millions of workers, particularly gig workers, informal traders, and self-employed micro-entrepreneurs generate income outside standard payroll systems, making it difficult for lenders to verify their earnings or assess repayment capacity. Yimer (2025) notes that in many developing and low-income economies, informal credit markets remain dominant, often localized within small communities where competition among lenders is minimal and social relationships substitute for formal contracts. Although this study draws on developing economies, parallels are evident in U.S. informal sectors, where self-employed and cash-based earners often lack the data visibility needed for credit assessment.

Another major barrier is the digital and infrastructural divide, which inhibits alternative data collection even when potential sources exist. While data from mobile payments, e-commerce, or utility bills could theoretically enhance credit inclusion, lack of internet access, limited device ownership, and low digital literacy impede data generation. As Mulwa and Yahya (2025) observe, "unbanked populations rarely participate in digital activities and thus lack substantial digital footprints," constraining the effectiveness of AI-driven credit models that rely on such data. These infrastructural and digital gaps prevent the full integration of alternative datasets that could fairly assess creditworthiness beyond exclusionary, traditional indicators.

Self-exclusion further compounds these barriers. Psychological and social deterrents often cause low-income or minority applicants to refrain from seeking credit due to expectations of rejection. The Federal Reserve Bank of New York (2024) reported that the share of Americans discouraged from applying for needed credit rose to 6.0% in 2024, up from 5.2% in 2023, nearly returning to pre-pandemic levels. This self-exclusion behavior reduces credit applications, thereby limiting the data generation that could improve their visibility in lending systems and perpetuating their financial marginalization.

Also, collateral and cost constraints remain among the most tangible barriers to credit access. Traditional lenders often demand collateral or impose higher risk premiums for borrowers lacking conventional profiles. Collier et al. (2021) found that many borrowers are willing to sacrifice up to 40% of their potential loan amount to avoid pledging collateral, viewing it as a burdensome and risky requirement. Their analysis also showed that while collateralized loans reduce default rates by approximately 35%, these requirements disproportionately exclude borrowers without assets, particularly low-income or minority households, thereby reinforcing the credit gap. However, these structural, technological, and behavioral barriers continue to exclude marginalized groups from mainstream credit systems, highlighting the urgent need for inclusive, data-driven AI models that reflect diverse financial realities.

Data Asymmetry and the Challenge of Informal Economies

A persistent theme in credit access research is data asymmetry, the imbalance between the information available to lenders and the true financial behavior of borrowers. Traditional credit-scoring frameworks are designed for borrowers with measurable and documented income streams, stable employment, and recorded repayment histories. In informal or semi-formal economies, conventional credit assumptions often fail, leaving large populations unassessed or misjudged by models reliant on incomplete or biased data. Ozanne (2024) observes that regulatory environments themselves can shape borrowers' willingness to share personal financial data, an increasingly vital asset in markets where credit allocation hinges on the quality and transparency of information. When information asymmetry persists, lenders either charge higher premiums to offset uncertainty or exclude certain applicants entirely, thereby reinforcing financial inequality.

Informal economies, where income generation occurs outside official regulatory and reporting systems, pose a particular challenge to accurate credit assessment. The chapter "Informal Credit Market: A General Overview" emphasizes how borrowers often rely on informal financial channels such as rotating savings groups, familial lending, or micro-trade credit, mechanisms that rarely appear in credit bureau datasets (Yimer, 2025). These informal credit relationships, though essential to economic survival, exist in data shadows that limit their recognition by formal financial institutions. As a result, millions of otherwise creditworthy individuals remain invisible to mainstream lenders.

In this context, the emergence of alternative data, including mobile payment histories, utility records, rental transactions, and social-behavioral analytics offers new possibilities for mitigating data asymmetry. Studies have demonstrated that integrating these non-traditional data sources can enhance model performance. An example is Kyeong et al. (2022) and Alamsyah et al. (2025) which highlights that combining call-detail records and social-network analytics with traditional credit bureau data substantially improves the predictive accuracy of credit models, allowing for more granular insights into repayment potential. However, these gains come with important caveats. Inclusive credit modeling faces the dual challenge of responsibly using data that often skews toward digitally connected populations and overcoming unreliable conventional assessments in informal economies, where AI and machine learning offer promise, yet risk reinforcing inequality without transparent governance, inclusive data pipelines, and ongoing bias audits.

Comparative Insights: Financial Inclusion Trends in Emerging and Developed Markets

Cross-national research on financial inclusion emphasizes that disparities in credit access manifest differently between emerging and developed economies, yet share a common structural root: unequal visibility within formal financial systems. According to the Global Findex Database (World Bank, 2021), approximately 1.4 billion adults worldwide remain unbanked, with more than half residing in populous developing nations such as India, Indonesia, and Nigeria (Adam et al., 2025; World Bank, 2025). Despite global account ownership rising to 76%, many individuals remain excluded from credit markets due to limited documentation, weak financial infrastructure, or informal employment patterns.

In rising markets, the exclusion challenge is closely tied to the credit gap facing micro, small, and medium enterprises (MSMEs), which typically account for over 90% of registered firms and form the backbone of job creation and income generation. Yet these firms often encounter constrained access to growth capital. In Indonesia, for instance, financial exclusion continues to undermine household resilience and restrict human capital investment, while simultaneously impeding the productivity of nearly 64 million MSMEs that collectively face a formal credit shortfall exceeding IDR 1,600 trillion (Adam et al., 2025). Empirical literature also demonstrates a clear link between digital-payment adoption and improved credit inclusion outcomes. Chen and

Xiao (2025), examining rural China, found that digital payments increased farmers' likelihood of obtaining formal credit but also reduced dependence on informal lenders, suggesting that digital ecosystems can serve as credible substitutes for conventional financial histories.

Conversely, in developed economies, inclusion gaps persist despite advanced financial systems and widespread institutional infrastructure. The problem is particularly acute among populations with limited documentation or nontraditional income streams such as immigrants, gig workers, and racial minorities. In the United States, the Federal Deposit Insurance Corporation (FDIC) continues to track sizable unbanked and underbanked populations, a key indicator of persistent systemic barriers to credit access (Deichmann, 2025). Here, exclusion often stems not from infrastructural absence but from rigid credit models that fail to accommodate evolving work patterns and fragmented financial records. Despite differing forms of financial exclusion across contexts, the universal barrier of informational visibility demands that alternative data and advanced analytics be paired with strong governance to ensure ethical, inclusive credit systems that do not replicate existing inequalities.

Summary of Key Literature Gaps

Although traditional credit-scoring systems such as FICO and VantageScore have been extensively examined, relatively few studies assess their effectiveness within informal economies or among unbanked and underbanked populations where formal financial documentation is scarce. Rising research on alternative-data credit-scoring, drawing on mobile payment histories, call-detail records, social-media activity, and psychometric evaluations shows promise for expanding financial inclusion. However, these approaches face persistent methodological and governance challenges, including concerns about data representativeness, algorithmic bias, and transparency in model construction. Furthermore, cross-national and comparative analyses between emerging and developed markets, while valuable, often overlook the nuanced performance of credit models across distinct socio-economic and demographic segments. Most critically, there remains a lack of integrative research that explicitly connects improvements in data structures, such as the use of richer and more diverse alternative data, with the development of ethical governance frameworks to ensure accountability, fairness, and equity when deploying AI-driven credit systems for underserved populations.

III. Evolution Of AI In Financial Services

Machine Learning in Credit Risk Prediction

Machine learning (ML) has become one of the most transformative innovations in modern credit-risk modeling, offering superior predictive capacity compared to conventional statistical approaches such as logistic regression and scorecard modeling. Chang et al. (2024) demonstrate that XGBoost achieves an impressive predictive accuracy of 99.4%, shows how machine learning and deep learning algorithms can substantially enhance credit-risk analysis and enable lenders to make more informed, data-driven decisions. Similarly, Marcos et al. (2025) highlight that hybrid ML frameworks, combining supervised and unsupervised techniques significantly improve credit-score prediction for commercial clients when historical credit and behavioral data are integrated. This evolution illustrates how machine learning is redefining how financial institutions assess and manage credit risk, moving beyond static, rule-based systems toward dynamic, adaptive modeling architectures.

Chen (2024) reinforces these findings, showing that while traditional credit-scoring methods continue to serve as a baseline, ML models, particularly Random Forests demonstrate superior performance in handling nonlinear, high-dimensional datasets. Compared with Ridge Regression and Neural Networks, Random Forest models not only offer higher accuracy but also greater robustness in managing multicollinearity and missing data, though interpretability remains a concern. Supervised learning algorithms such as decision trees, random forests, gradient boosting, and support vector machines enhance predictive precision by uncovering complex, nonlinear relationships among borrower attributes—patterns that traditional linear models often fail to capture (Kozodoi et al., 2024; Gafsi, 2025; Agboola et al., 2024).

Moreover, AI-driven credit-risk systems are demonstrating quantifiable efficiency gains across multiple dimensions of financial risk management. According to Haosen et al. (2024), AI-powered credit models have improved predictive accuracy by up to 20%, accelerated anomaly detection in market-risk monitoring by 30%, reduced false positives in fraud detection by 60%, and improved favorable credit decisions by 40%. These gains illustrate how algorithmic models are not only enhancing accuracy but also optimizing operational efficiency and reshaping traditional credit-evaluation paradigms.

Deep Learning and Neural Network Applications in Finance

Deep learning has become one of the most powerful paradigms in modern finance, enabling the modeling of complex, nonlinear relationships that traditional statistical and machine-learning methods often fail to capture. While much of the early literature on financial artificial intelligence focused on conventional architectures such as multilayer perceptrons and feedforward neural networks, recent developments emphasize advanced architectures—including Transformers, Generative Adversarial Networks (GANs), and Deep Reinforcement

Learning (DRL)—that are redefining scalability, precision, and interpretability in data-intensive financial environments (Mienye et al., 2024). These architectures have extended the frontier of financial analytics beyond traditional domains, powering high-frequency trading, portfolio optimization, credit risk modeling, and fraud detection.

Deep neural networks (DNNs) and related architectures have become increasingly central to understanding complex financial interdependencies. Debidutta et al. (2024) demonstrate that deep learning can effectively model the propagation of systemic shocks across interconnected financial networks, supporting the development of early-warning systems that enhance macroprudential surveillance. Within credit markets, DNNs excel at capturing nonlinear correlations between borrower characteristics and repayment behaviors, allowing for more nuanced segmentation and risk differentiation than conventional regression-based models.

The growing sophistication of deep learning architectures, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) has opened new avenues for financial applications. RNNs are particularly suited to modeling sequential dependencies in time-series data such as transaction histories, credit repayments, and spending behavior, since they maintain a "memory" of past states that informs future predictions (Shi et al., 2022). In contrast, CNNs specialize in extracting hierarchical spatial features, making them useful for applications where structured and visual data intersect, such as document verification or graph-based fraud detection. Gür et al. (2025) show that CNN-based models outperform traditional methods in tasks requiring high-precision pattern recognition and anomaly detection, enhancing both the accuracy and interpretability of financial decision systems.

Deep learning models have consistently demonstrated superior generalization and predictive power over conventional machine learning algorithms, particularly when trained on large, high-dimensional datasets with sufficient computational capacity (Cardenas-Ruiz et al., 2022). In credit scoring, hybrid neural architectures that integrate structured financial data with behavioral and psychometric inputs have proven particularly effective in addressing "thin-file" challenges. Kimani et al. (2024) find that hybrid models combining RNNs and Deep Neural Networks (DNNs) significantly improve default prediction accuracy and fairness, offering a promising pathway for financial inclusion by reducing the exclusion of individuals with limited credit histories. Similarly, Jahanzaib et al. (2024) report that hybrid systems combining Artificial Neural Networks (ANNs) with traditional statistical techniques like Logistic Regression often outperform standalone models, achieving predictive accuracies ranging between 82.79% and 90.30% depending on feature selection and optimization algorithms.

Hayashi (2022) further demonstrates the potential of integrating image-based analytics into financial modeling by transforming tabular credit data into visual representations and applying CNNs for feature extraction. This approach not only improved predictive accuracy compared to benchmark models like logistic regression and random forests but also provided new insights into multidimensional relationships within credit data. Yet, these systems pose unique challenges in terms of overfitting, transparency, and explainability, particularly when applied to regulated domains like consumer credit.

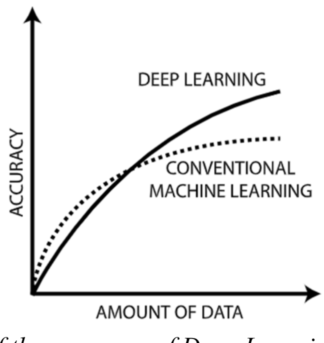

Figure 2: *Illustrative comparison of the accuracy of Deep Learning against typical machine learning algorithm.*
Source: *Cardenas-Ruiz et al. (2022)*

Natural Language Processing (NLP) and Behavioral Analytics in Credit Profiling

AI-driven natural language processing (NLP) and behavioral analytics extend credit assessment beyond traditional scoring by incorporating qualitative and unstructured information into borrower profiling. NLP techniques enable lenders to detect financial stress signals, such as job loss notifications, medical-expense narratives, or shifts in tone in customer communication by analyzing social media posts, customer-service transcripts, and feedback comments (Song & Esther, 2022). Combining these behavioral and sentiment insights with structured transaction data, lenders can enhance the inclusivity and precision of credit decisions, potentially capturing creditworthiness of individuals who would otherwise remain invisible to traditional models.

Financial institutions increasingly use NLP not only for borrower profiling but also to automate due-diligence and transaction monitoring processes. For example, NLP tools can extract indicators of reputational or operational risk from unstructured text, such as patterns suggestive of money-laundering or illicit behaviour by identifying suspicious linguistic patterns (Oyedokun et al., 2024). Meanwhile, behavioral analytics harness "digital exhaust", such as mobile-app usage patterns, spending rhythms, device location history, and psychometric cues to infer financial reliability. As Goyal & Saxena (2021) note, combining digital-footprint data with advanced analytics enables lenders and fintech firms to blend historical financial behaviour with real-time signals, thereby improving predictions of repayment potential and expanding credit access for underserved individuals and small businesses.

NLP techniques such as sentiment analysis and semantic modelling are increasingly applied to borrower narratives, customer-service exchanges, and online communications (Nayak, 2024; Olujimi & Ade-Ibijola, 2023). Integrating these NLP-powered analytics into banking operations can generate actionable insights, improve service delivery, and enable personalized customer experiences that strengthen lender-customer relationships and support competitive differentiation (Suresh et al., 2024). Similarly, behavioral analytics research indicates that metrics such as spending regularity, savings behaviour, app-based financial-management usage and insurance participation are important empirical drivers of personal financial management on digital platforms (Chhillar & Arora, 2022). Recent work by Fine (2024) and Alamsyah et al. (2025) highlights that incorporating psychometric and linguistic markers significantly enhances prediction accuracy for underbanked and thin-file consumers, pointing to a viable pathway toward more inclusive credit profiling. However despite their potential, applying NLP and behavioral analytics in credit scoring presents key challenges, including the uneven representativeness of digital-exhaust data which may exclude older, rural, or digitally disconnected populations and unresolved ethical and regulatory concerns around privacy, fairness, and the explainability of using unstructured personal data in lending decisions.

Advantages and Challenges of AI Adoption in Credit Markets

AI deployment in credit markets delivers substantial operational benefits but also raises complex ethical and regulatory challenges. Its effectiveness depends on the quality of training data, model architecture, and implementation practices. While AI enhances prediction accuracy, processing efficiency, and scalability in credit assessment through the integration of alternative and behavioral data, it simultaneously introduces critical risks related to data quality, bias propagation in foundation models, and privacy vulnerabilities, especially when handling unstructured inputs that heighten data leakage concerns (Georg et al., 2024). Despite measurable gains in predictive performance, AI systems continue to face persistent issues of bias, limited explainability, cybersecurity risks, and regulatory non-compliance (Adewuyi et al., 2023). Empirical studies further indicate that algorithmic decision-making can inadvertently reproduce historical inequities embedded in financial data, thereby reinforcing systemic disparities in credit access (Jha, 2024; Belenguer, 2024). Achieving sustainable adoption thus requires a balance between innovation and governance through responsible AI frameworks, transparent model design, and adherence to fair-lending and data protection principles.

IV. AI-Driven Credit Scoring Frameworks

Model Architecture and Design Principles

Modern AI credit models leverage ensemble learning, neural networks, and hybrid architectures to enhance predictive accuracy while maintaining interpretability. Traditional credit scoring techniques, such as logistic regression and decision trees have been significantly advanced through machine learning approaches like ensemble models, support vector machines, and neural networks that utilize large-scale and alternative data sources, including social media activity, transaction histories, and demographic indicators, to deliver more comprehensive assessments of borrower creditworthiness (Gates et al., 2025).

Gradient boosting and random forest classifiers are frequently applied to structured financial datasets, with recent results showing that a combination of random forest and gradient boosting achieves a test accuracy of 94.74%, outperforming state-of-the-art models such as k-nearest neighbor, decision tree, support vector, and naive Bayes classifiers (Dağıstanlı et al., 2024). Deep neural networks (DNNs), known for their ability to capture complex nonlinear relationships and adapt to low-dimensional structures, continue to redefine the boundaries of credit modeling (Bhattacharya et al., 2023). Their growing utility in estimating structured regression functions and uncovering hidden feature interactions has been established across multiple financial datasets (Kozodoi et al., 2024).

Hybrid architectures that merge decision trees with neural embeddings further enhance adaptability across borrower segments. Dağıstanlı et al. (2024) demonstrate that ensemble configurations combining decision trees and neural networks, particularly through boosted-stacking strategies, significantly improve ranking performance and flexibility, offering a powerful balance between accuracy and computational efficiency. Similarly, Gür et al. (2025) find that integrating classification and clustering techniques through hybrid frameworks that combine supervised and unsupervised learning methods strengthens the predictive performance of credit scoring systems.

Data Preprocessing, Feature Engineering, and Variable Selection

Effective AI-driven credit scoring frameworks rely profoundly on rigorous data preprocessing and feature engineering processes that transform diverse, often unstructured data sources into standardized and predictive features. These stages are essential for optimizing model performance, interpretability, and fairness in credit decision-making (Shukla & Gupta, 2024). Through advanced preprocessing, datasets ranging from mobile money transactions and call-detail records to digital behavioral traces are cleaned, normalized, and harmonized to ensure consistency and reduce bias across borrower segments.

Feature engineering are critical contributor involved in extracting meaningful representations from heterogeneous inputs. Techniques such as Recursive Feature Elimination (RFE), Information Gain (IG), and ReliefF are commonly employed to identify the most informative variables while mitigating overfitting and ensuring model generalizability. RFE is a flexible dimensionality reduction technique that iteratively eliminates less important features using models such as support vector regression, random forest, or linear regression. It offers advantages over traditional backward elimination by accommodating multiple algorithmic frameworks and allowing multi-feature pruning in each iteration (Niquini et al., 2023).

In contrast, Information Gain (IG) measures the relative importance of features in high-dimensional datasets and is particularly useful for evaluating variable relevance in credit risk prediction. However, its tendency to overemphasize features with high numerical variance requires selective application during model tuning to preserve fairness and interpretability (Shih et al., 2022). ReliefF complements these methods by evaluating feature relevance through local neighborhood analysis but may exhibit reduced classification accuracy when applied to noisy or non-uniformly distributed datasets (Aggarwal et al., 2023).

Additional preprocessing techniques—such as data normalization, Synthetic Minority Over-sampling Technique (SMOTE) to correct class imbalance, and Principal Component Analysis (PCA) for dimensionality reduction, further enhance model robustness and generalization capacity (SWASTIK, 2025; Mean & Ivan Chang, 2025). Together, these processes form the backbone of responsible and high-performing AI credit scoring, ensuring that algorithmic predictions reflect meaningful, unbiased financial behavior rather than data distortions or demographic artifacts.

Model Evaluation Metrics: Accuracy, Precision, Recall, and AUC

Evaluating AI-driven credit scoring models requires a multidimensional approach that extends beyond mere accuracy. In practice, classification models are assessed using a combination of metrics—such as precision, recall (sensitivity), specificity, false positive rate, F1 score, Receiver Operating Characteristic (ROC) curve, and the Area Under the Curve (AUC)—which collectively offer a holistic view of a model's capacity to correctly identify both positive and negative cases. Muraina et al. (2023) illustrated this in the context of diabetes prediction, emphasizing that reliance on accuracy alone can obscure weaknesses in class discrimination. In a 2025 study, Kang et al. evaluated credit risk prediction models using accuracy, precision, recall, F1-score, and ROC AUC, finding that LightGBM achieved the most balanced performance—with an accuracy of 0.9764, precision of 0.9747, and recall of 0.9503. Their permutation importance analysis identified interest, credit type, interest rate spread, and upfront charges as the most influential determinants of loan default.

Precision and recall jointly indicate model reliability in distinguishing creditworthy borrowers from potential defaulters, while the AUC-ROC provides a comprehensive measure of discriminative power across thresholds. Zhou (2022) found that Decision Tree models delivered the highest precision but the lowest AUC, Random Forest models achieved superior accuracy but lower recall, and XGBoost surpassed both by producing the highest recall and AUC. Consistent with these findings, comparative analyses show that machine learning–based scoring frameworks generally outperform traditional logistic regression models in AUC performance, reflecting their superior sensitivity to nonlinear financial behaviors (Marcos et al., 2025; Kozodoi et al., 2024).

Interpretability: Explainable AI and Model Transparency

As AI adoption in credit assessment expands, explainability has become both a regulatory and ethical imperative. de Lange et al. (2022) found SHAP values to be the most robust and reliable method for explaining feature importance in credit scoring models, outperforming LIME in observation discrimination. However, they noted that KernelSHAP's high computational cost limits its scalability in high-dimensional datasets, while LIME may suffer from instability and local inconsistency. SHAP (SHapley Additive exPlanations) is a model-agnostic technique that attributes each feature's contribution to the model's prediction, offering granular interpretability across various machine learning algorithms (Shreya & Pathak, 2025).

Explainable AI (XAI) techniques such as SHAP and LIME enable financial institutions to trace the logic behind model outputs, identify the most influential predictors of creditworthiness, and justify lending decisions to both regulators and consumers. As AI models become more complex, the distinction between interpretability, understanding how a model operates and explainability, understanding why it produces a specific decision—has gained critical importance. This distinction has driven research toward inherently transparent systems that balance predictive accuracy with fairness, accountability, and compliance (Dhanesh et al., 2025). Transparent, interpretable models not only enhance consumer trust and mitigate bias but also ensure adherence to evolving regulatory frameworks such as the EU AI Act and the U.S. Consumer Financial Protection Bureau's (CFPB) fairness standards, effectively addressing the "black-box" challenge in automated lending.

V. Case Studies: Zest AI, Tala, Branch, Fairmoney, And Jumo

Several fintech firms have shown examples of the successful deployment of AI-driven credit scoring frameworks to advance financial inclusion. Zest AI uses explainable machine learning to improve underwriting accuracy and bias control, enabling 2–4x more accurate risk ranking and up to a 25% increase in approval rates without raising default risk. Its designed models, built on ethically sourced data, accurately assess 98% of American adults while reducing risk by over 20% when approval levels remain constant (Zest AI, n.d).Tala and Branch leverage alternative data from mobile usage to build credit profiles for unbanked individuals in Africa and Asia, enabling financial inclusion for millions traditionally excluded from formal lending systems (Boafo et al., 2025). FairMoney is a digital lending platform that uses behavioral analytics and mobile-based data to assess credit risk and issue microloans to underbanked individuals in Nigeria and India, even without formal credit histories (Obiya, 2024; TechCrunch, 2021). Similarly, Jumo utilizes machine learning models on mobile-money transaction data to deliver credit services to over millions of users across Africa, using AI-driven systems as a tool that can bridge formal credit access gaps reducing error by 80% (Jumo, 2024). These frameworks of FinTech companies shows the effect of AI's technical sophistication which are rooted in advanced model architectures, transparent interpretability tools, and real-time analytics, thereby redefining inclusivity in global credit markets when balanced with responsible data governance and ethical deployment.

VI. Ethical, Legal, And Governance Considerations

The increasing integration of AI into credit markets introduces complex ethical, legal, and governance challenges centered on algorithmic fairness, accountability, and regulatory compliance. Algorithmic credit scoring (ACS) leverages machine learning and smartphone-derived data to enhance efficiency and predictive accuracy in assessing borrower risk, yet its expansion raises serious concerns over transparency, bias, and data privacy (Nicolas & Jodi, 2023). While such systems improve prediction accuracy, they can inadvertently perpetuate systemic inequities when trained on historically biased or unbalanced datasets. The European Union's AI Act adopts a tiered risk-based regulatory framework, prohibiting AI systems with unacceptable risks, imposing strict obligations on high-risk applications in sectors such as finance and healthcare, and applying lighter oversight to low-risk systems. However, the framework overlooks potential harms from seemingly benign AI applications, such as those introduced in social media, leaving unresolved questions about oversight and democratic accountability (Bartsch et al., 2025).

Algorithm-driven financial systems provide powerful tools for automation and predictive analytics, yet their growing influence on financial stability and market operations introduces new ethical concerns, particularly regarding embedded bias in historical data (Arif et al., 2025). Addressing these issues requires robust ethical frameworks that promote data integrity, fairness, and transparency in automated lending. Bias mitigation strategies including algorithmic fairness testing, rigorous model audits, diverse and representative training datasets, and interpretable modeling, are essential to ensuring both trust and compliance. Importantly, AI-driven credit scoring can simultaneously serve as a catalyst for expanding financial inclusion when responsibly governed (Umeaduma & Adeniyi, 2025).

As credit-scoring systems increasingly rely on alternative and behavioral data that may encode sensitive demographic or socioeconomic attributes, data ethics has become central to minimizing disparate impacts and ensuring equitable access to credit (Julien & Owusu-Berko, 2025). Regulatory frameworks such as the European Union's General Data Protection Regulation (GDPR), the California Consumer Privacy Act (CCPA), and the U.S. Fair Credit Reporting Act (FCRA) establish foundational standards for privacy, transparency, and consumer rights, mandating that automated credit decisions remain explainable and contestable. Nevertheless, enforcement gaps persist across jurisdictions, particularly concerning opaque algorithmic models and cross-border data flows (Experian, 2024; European Commission, 2024; EUR-Lex, 2024). Responsible AI governance therefore requires ongoing auditability, explainability, and accountability throughout the AI lifecycle to mitigate social and systemic risks. Yet, as Gunasekara et al. (2025) observe, implementing these standards remains difficult due to fragmented governance frameworks and the proliferation of competing principles across sectors and stakeholders. Ultimately, human oversight remains indispensable in automated credit systems, serving as a safeguard against model overreach and ensuring that credit decisions reflect not only computational precision but also ethical and contextual judgment.

VII. Comparative Analysis: Traditional Vs. Ai-Driven Credit Scoring Systems

The evolution from traditional credit-scoring models to AI-driven systems marks a major shift in predictive accuracy, efficiency, and inclusivity. Conventional credit risk models like logistic regression and rule-based scorecards are limited by linear assumptions and narrow data inputs, whereas machine learning techniques, especially Random Forests excel at capturing complex, nonlinear patterns in high-dimensional datasets for more accurate assessments (Chen, 2024). In contrast, AI-powered frameworks employing machine learning and deep learning algorithms such as Random Forests, Gradient Boosting, and XGBoost demonstrate superior predictive performance and adaptability to complex, nonlinear data patterns. Studies by Chang et al. (2024) and Marcos et al. (2025) reveal that hybrid ML models can achieve accuracy levels exceeding 99% in credit risk prediction, outperforming traditional models by leveraging alternative and behavioral data sources. These models identify intricate feature interactions and contextual dependencies that conventional statistical techniques often overlook.

In addition to improved predictive accuracy, AI-driven credit scoring delivers significant cost savings and scalable operations. Automated data preprocessing and feature engineering techniques, such as Recursive Feature Elimination (RFE), Information Gain, and SMOTE balancing rationalizing workflows and reduce human intervention (Shukla & Gupta, 2024; Niquini et al., 2023; Aggarwal et al., 2023). Financial institutions deploying ensemble and deep learning architectures have achieved faster decision cycles, reduced underwriting costs, and enhanced fraud detection through real-time model updates and continuous learning (Emmanuel, 2025). Also, the use of NLP and behavioral analytics in credit profiling extends the scope of inclusion by incorporating unstructured data from mobile usage, transaction histories, and psychometric cues, enabling fairer assessments of thin-file and underbanked borrowers (Song & Esther, 2022; Fine, 2024; Alamsyah et al., 2025). Firms like FairMoney and Tala are integrating the shift in behavioral analytics and real-time repayment modeling to expand microcredit access across emerging markets (Obiya, 2024; Boafo et al., 2025; TechCrunch, 2021).

However, while AI-driven systems improve adaptability and inclusivity, they introduce new challenges in interpretability, data ethics, and governance. Explainable AI (XAI) methods, such as SHAP and LIME have become essential in reconciling accuracy with transparency, providing interpretive frameworks that align with regulatory expectations under the Fair Credit Reporting Act (FCRA) and the General Data Protection Regulation (GDPR) (de Lange et al., 2022; Shreya & Pathak, 2025). Yet issues of algorithmic bias, data quality, and model accountability persist, as observed in Georg et al. (2024) and Jha (2024) article, who warn that poorly designed or inadequately monitored models can reproduce systemic inequities infused in historical data. Comparative performance analyses consistently affirm that while AI-based credit models outperform traditional systems in predictive accuracy and operational scale, their sustainable adoption hinges on ethical governance, fairness audits, and human oversight (Bartsch et al., 2025; Gunasekara et al., 2025). Thus, the future of credit risk management hinges on harmonizing traditional models with AI's analytical power, combining human oversight and regulatory compliance with machine-driven precision and flexibility.

VIII. Proposed Model For Inclusive, Ethical AI Credit Scoring

In this study, a practical model is proposed for inclusive and ethical AI-driven credit scoring which is designed as a hybrid framework that combines predictive accuracy with transparency, fairness, and accountability. Conceptually, the framework integrates machine learning–based risk prediction models with fairness-aware algorithms and explainable AI (XAI) techniques to ensure that automated credit decisions remain both data-driven and ethically sound. Building on the strengths of existing credit scoring systems like Zest AI, Tala, and FairMoney, this model addresses core challenges such as bias mitigation, interpretability, and regulatory compliance (de Lange et al., 2022; Umeaduma & Adeniyi, 2025). Inclusive and ethical AI in credit scoring should incorporates real-time data ingestion pipelines that capture conventional and alternative variables, varying from credit history and repayment patterns to behavioral analytics, while applying dynamic reweighting mechanisms to prevent discrimination against marginalized borrowers.

To strengthen this, integration of fairness metrics into the AI workflow is paramount. Fairness is operationalized through quantitative metrics such as demographic parity, equal opportunity difference, and disparate impact ratio, which are computed at multiple stages of model development. These fairness indicators guide data preprocessing, model training, and validation, ensuring the system learns equitable, non-bias decision patterns and transparency across demographic segments (Nicolas & Jodi, 2023; Dhanesh et al., 2025). Furthermore, the framework is designed with explainability tools like SHAP and LIME within its evaluation layer, enabling lenders to trace model reasoning and verify the contribution of each feature to the final decision, which is critical for maintaining regulatory trust under frameworks such as the GDPR, CCPA, and the Fair Credit Reporting Act (de Lange et al., 2022; Shreya & Pathak, 2025; Experian, 2024; European Commission, 2024).

A dynamic data pipeline lies at the heart of this model, enabling continuous model retraining and real-time risk assessment. This adaptability supports ongoing learning from borrower behavior and repayment outcomes, enhancing predictive performance and inclusivity. The integration of data from mobile transactions, digital wallets, and alternative credit indicators expands access to credit for underbanked populations while preserving strong risk differentiation. Continuous learning mechanisms reflect the principles behind advanced AI credit models like LightGBM, XGBoost, and Random Forests, which consistently outperform traditional approaches in recall and AUC metrics (Kang et al., 2025; Zhou, 2022; Marcos et al., 2025).

Model validation and bias correction are achieved through multi-layered auditing procedures. Post-deployment, the system undergoes routine fairness audits and counterfactual analysis to detect drift or arising biases in data representation or decision outcomes. These findings inform recalibration strategies that sustain equitable lending practices over time. This model also encourages human oversight at critical decision junctures, ensuring that AI recommendations are reviewed and contextualized by human analysts to balance computational precision with ethical reasoning (Gunasekara et al., 2025).

To implement this strategy in rising markets, the roadmap involves three progressive stages, first is establishing data governance structures aligned with regional regulatory frameworks, secondly, deploying modular AI scoring engines that can operate on limited infrastructure; and Lastly, instituting collaborative oversight involving fintech firms, banks, and regulators to promote transparency and inclusivity. This model provides a scalable blueprint for financial institutions seeking to combine advanced analytics with ethical safeguards, ensuring that AI-driven credit scoring not only enhances operational efficiency but also promotes financial inclusion and social equity across diverse markets similar to Arif et al. (2025) and Bartsch et al.(2025) proposed framework.

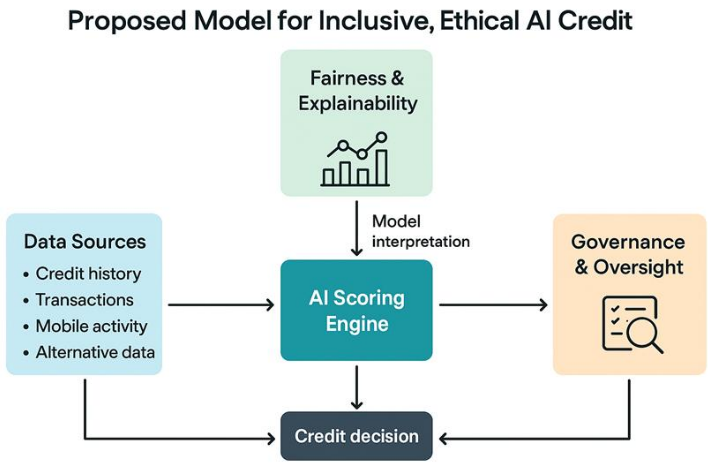

Figure 3: *Proposed Model for Inclusive, Ethical AI Credit*

IX. Discussion

The integration of AI into credit markets presents transformative strategic implications for fintech innovation, regulatory policy, and financial inclusion. Fintechs are increasingly positioned as catalysts for inclusion by deploying AI credit models that leverage nontraditional data sources such as mobile transactions and behavioral analytics to evaluate creditworthiness among populations historically excluded from formal finance similar to the observational report of by Nicolas & Jodi, (2023). These models enhance predictive accuracy and scalability (Gates et al., 2025; Dağıstanlı et al., 2024) and also introduce new paradigms for personalized credit products and risk-based pricing in underserved markets.

For regulators and development agencies, the rise of AI-enabled credit assessment underscores the urgent need for adaptive policy frameworks that reconcile innovation with consumer protection. Regulations like the GDPR, CCPA, and FCRA (European Commission, 2024; Experian, 2024) provide foundational principles for transparency and accountability, yet the rising economies require context-specific governance models to mitigate algorithmic bias, ensure data integrity, and promote fair access to financial services (Bartsch et al., 2025). Development agencies contribute significantly by supporting capacity building in responsible AI deployment and fostering open-data ecosystems that promote equitable participation.

Collaboration between public and private sectors also remains essential for sustainable AI-driven credit ecosystems. Partnerships among banks, fintechs, and regulators can accelerate innovation while maintaining ethical guardrails, enabling shared infrastructures for data verification, model validation, and inclusive credit reporting (Umeaduma & Adeniyi, 2025).

Looking ahead, research on AI-enabled financial inclusion must focus on explainability, fairness metrics, and longitudinal impact evaluation. Future studies should assess more than performance outcomes, it should also focus on the socio-economic implications of algorithmic lending, ensuring that technological advancement aligns with the broader goal of equitable financial empowerment.

X. Conclusion

This study highlights the transformative potential of artificial intelligence in redefining credit scoring, enhancing predictive accuracy, and broadening access to finance for underserved populations. Through the integration of machine learning, deep learning, and behavioral analytics, AI-driven credit models outperform traditional frameworks by leveraging dynamic, alternative data sources that capture more refined indicators of creditworthiness. However, these advancements also introduce critical ethical and governance challenges, particularly around algorithmic bias, data privacy, and model explainability. The comparative analysis highlights that while AI systems deliver greater efficiency and inclusivity, their sustainability depends on robust governance structures and continuous oversight to prevent systemic inequities.

From a policy and practice perspective, financial regulators and fintech innovators must jointly prioritize the development of fair, transparent, and auditable AI frameworks. Implementing fairness-aware algorithms, mandatory explainability standards, and regular bias audits can foster trust and ensure compliance with evolving global regulatory frameworks such as the GDPR, CCPA, and FCRA. Collaboration between public institutions, development agencies, and private-sector actors is essential to create inclusive data ecosystems that enable responsible innovation while safeguarding consumer rights.

In the long term, ethical AI-driven credit access holds the promise of reshaping global financial systems toward greater inclusion and equity. As AI technologies mature, the emphasis must shift from mere predictive power to human-centered design, embedding fairness, accountability, and transparency into every stage of the credit lifecycle. If guided by sound governance and interdisciplinary cooperation, AI can serve as a powerful instrument for democratizing finance, bridging economic divides, and advancing sustainable development across rising and developed markets alike.

Reference

[1]. Adam, L., Sarana, J., Suyatno, B., Soekarni, M., Suryanto, J., Ermawati, T., Saptia, Y., Adityawati, S., Mychelisda, E., Pamungkas, Y., Abdillah, M. R. N., Angelia, L., & Thoha, M. (2025). Driving Financial Inclusion In Indonesia With Innovative Credit Scoring. Journal Of Risk And Financial Management, 18(8), 442. Https://Doi.Org/10.3390/Jrfm18080442

[2]. Adewuyi, Ademola & Ajuwon, Ayodeji & Oladuji, Tolulope Joyce & Akintobi, Abiola. (2023). Advances In Financial Inclusion Models: Expanding Access To Credit Through AI And Data Analytics. International Journal Of Advanced Multidisciplinary Research And Studies. 3. 1827-1842. 10.62225/2583049X.2023.3.6.4403.

[3]. Alamsyah, A., Hafidh, A. A., & Mulya, A. D. (2025). Innovative Credit Risk Assessment: Leveraging Social Media Data For Inclusive Credit Scoring In Indonesia's Fintech Sector. Journal Of Risk And Financial Management, 18(2), 74. Https://Doi.Org/10.3390/Jrfm18020074

[4]. Arif Perdana, Saru Arifin, Novi Quadrianto. (2025). Algorithmic Trust And Regulation: Governance, Ethics, Legal, And Social Implications Blueprint For Indonesia's Central Banking. Technology In Society, Volume 81, 102838, ISSN 0160-791X. Https://Doi.Org/10.1016/J.Techsoc.2025.102838.

[5]. Arora, S. (2023, September 19). What Is Equifax Credit Score? Everything You Need To Know. Surepass. Https://Surepass.Io/Blog/What-Is-Equifax-Credit-Score/

[6]. Baozhen Chen, Jialin Xiao. (2025). Digital Payments Enhance Both Formal And Informal Credit Access For Rural Households: Evidence From China. Front. Sustain. Food Syst., Sec. Social Movements, Institutions And Governance, Volume 9 - 2025 | Https://Doi.Org/10.3389/Fsufs.2025.1676462

[7]. Bartsch, S., Behn, O., Benlian, A. Et Al. (2025). Governance Of High-Risk AI Systems In Healthcare And Credit Scoring. Bus Inf Syst Eng 67, 563–581 Https://Doi.Org/10.1007/S12599-025-00944-4

[8]. Belenguer L. (202). AI Bias: Exploring Discriminatory Algorithmic Decision-Making Models And The Application Of Possible Machine-Centric Solutions Adapted From The Pharmaceutical Industry. AI Ethics. 2022;2(4):771-787. Doi: 10.1007/S43681-022-00138-8. Epub 2022 Feb 10. PMID: 35194591; PMCID: PMC8830968.

[9]. Bhattacharya, Sohom & Fan, Jianqing & Mukherjee, Debarghya. (2023). Deep Neural Networks For Nonparametric Interaction Models With Diverging Dimension. 10.48550/Arxiv.2302.05851.

[10]. Cardenas-Ruiz, Carlos & Mendez-Vazquez, Andres & Ramirez-Solis, Luis. (2022). Explainable Model Of Credit Risk Assessment Based On Convolutional Neural Networks. 10.1007/978-3-031-19493-1_7.

[11]. CNBC (2025). What Is A FICO Score And Why Is It Important? CNBC Select. Https://Www.Cnbc.Com/Select/What-Is-Fico-Score/

[12]. Chang, V., Sivakulasingam, S., Wang, H., Wong, S. T., Ganatra, M. A., & Luo, J. (2024). Credit Risk Prediction Using Machine Learning And Deep Learning: A Study On Credit Card Customers. Risks, 12(11), 174. Https://Doi.Org/10.3390/Risks12110174

[13]. Chen, Ziqing. (2024). Machine Learning In Credit Risk Assessment: A Comparative Analysis Of Different Models (October 31, 2024). Available At SSRN: Https://Ssrn.Com/Abstract=5006192 Or Http://Dx.Doi.Org/10.2139/Ssrn.5006192

[14]. Chhillar, Neetu & Arora, Swaranjeet. (2022). Personal Financial Management Behavior Using Digital Platforms And Its Domains. Journal Of Financial Management, Markets And Institutions. 10. 10.1142/S2282717X22500098.

[15]. Dağıstanlı, Hakan & Özen, Figen & Saracoglu, Ilkay. (2024). Forecasting Sustainability Reports With Financial Performance Indicators Using Random Forest For Feature Selection And Gradient Boosting For Learning. Savunma Bilimleri Dergisi. 10.17134/Khosbd.1492365.

[16]. De Lange, P. E., Melsom, B., Vennerød, C. B., & Westgaard, S. (2022). Explainable AI For Credit Assessment In Banks. Journal Of Risk And Financial Management, 15(12), 556. Https://Doi.Org/10.3390/Jrfm15120556

[17]. Debidutta Pattnaik, Sougata Ray, Raghu Raman. (2024). Applications Of Artificial Intelligence And Machine Learning In The Financial Services Industry: A Bibliometric Review. Heliyon, Volume 10, Issue 1, E23492, ISSN 2405-8440. Https://Doi.Org/10.1016/J.Heliyon.2023.E23492.

[18]. Dhanesh Ramachandram, Himanshu Joshi, Judy Zhu, Dhari Gandhi, Lucas Hartman, Ananya Raval. (2025). Transparent AI: The Case For Interpretability And Explainability. Https://Arxiv.Org/Html/2507.23535v1#:~:Text=Interpretability%20refers%20to%20how%20easily,1).

[19]. Emmanuel, Mayowa. (2025). Deep Learning Architectures For Real-Time Anomaly Detection In Financial Transactions.

[20]. EUR-Lex. (2024). Official Journal Of The European Union. Retrieved November 11, 2025, FromHttps://Eur-Lex.Europa.Eu/Todayoj/
[21]. Experian. (2024). Fair Credit Reporting Act (FCRA). Ask Experian. Retrieved November 11, 2025, From Https://Www.Experian.Com/Blogs/Ask-Experian/Credit-Education/Report-Basics/Fair-Credit-Reporting-Act-Fcra/
[22]. Experian. (2024). FICO Score: What It Is And Why It's Important. Https://Www.Experian.Com/Blogs/Ask-Experian/Fico-Score-What-It-Is-And-Why-Its-Important/
[23]. Experian. (2025). My Credit Score: What It Is And Why It Matters. Https://Www.Experian.Com/Blogs/Ask-Experian/Credit-Education/Score-Basics/My-Credit-Score/
[24]. Federal Reserve Bank Of New York. (2024, November 18). 2024 SCE Credit Access Survey Shows Increase In Discouraged Borrowers. Https://Www.Newyorkfed.Org/Newsevents/News/Research/2024/20241118
[25]. Fine, S. (2024). Character Counts: Psychometric-Based Credit Scoring For Underbanked Consumers. Journal Of Risk And Financial Management, 17(9), 423. Https://Doi.Org/10.3390/Jrfm17090423
[26]. Foo Hui Mean And Yuan-Chin Ivan Chang. (2025). A Survey: Potential Dimensionality Reduction Methods For Data Reduction. Https://Arxiv.Org/Html/2502.11036
[27]. Gafsi, N. (2025). Machine Learning Approaches To Credit Risk: Comparative Evidence From Participation And Conventional Banks In The UK. Journal Of Risk And Financial Management, 18(7), 345. Https://Doi.Org/10.3390/Jrfm18070345
[28]. Gates, Noah And Flynn, Will And Flynn, Will, A Comprehensive Review Of Artificial Intelligence-Driven Credit Risk Modeling: From Traditional Scoring To Explainable Machine Learning In Modern Banking Systems (August 28, 2025). Available At SSRN: Https://Ssrn.Com/Abstract=5414214 Or Http://Dx.Doi.Org/10.2139/Ssrn.5414214
[29]. Georg Leitner, Jaspal Singh, Anton Van Der Kraaij And Balázs Zsámboki. (2024). The Rise Of Artificial Intelligence: Benefits And Risks For Financial Stability. Https://Www.Ecb.Europa.Eu/Press/Financial-Stability-Publications/Fsr/Special/Html/Ecb.Fsrart202405_02~58c3ce5246.En.Html
[30]. Goodness, Shalom & Shan, Abraham & Oladele, Sunday & Stark, Bright. (2025). AI And Credit Scoring: Assessing The Fairness And Transparency Of Machine Learning Models In Lending Decisions.
[31]. Goyal, Somya & Saxena, Arti. (2021). Creditworthiness Assessment Using Natural Language Processing. 10.4018/978-1-7998-7728-8.Ch007.
[32]. Grace W. Kimani, J.K Mwai, E. Mwangi. (2024). A Deep Learning Based Hybrid Model Development For Enhanced Credit Score Prediction. DOI: Https://Doi.Org/10.51584/IJRIAS.2024.907024
[33]. Gunasekara, L., El-Haber, N., Nagpal, S., Moraliyage, H., Issadeen, Z., Manic, M., & De Silva, D. (2025). A Systematic Review Of Responsible Artificial Intelligence Principles And Practice. Applied System Innovation, 8(4), 97. Https://Doi.Org/10.3390/Asi8040097
[34]. Gür, Y.E., Toğaçar, M. & Solak, B. (2025). Integration Of CNN Models And Machine Learning Methods In Credit Score Classification: 2D Image Transformation And Feature Extraction. Comput Econ 65, 2991–3035 (2025). Https://Doi.Org/10.1007/S10614-025-10893-5
[35]. Haosen Xu, Kaiyi Niu, Tianyi Lu , & Siyang Li. (2024). Leveraging Artificial Intelligence For Enhanced Risk Management In Financial Services: Current Applications And Future Prospects. Engineering Science & Technology Journal P-ISSN: 2708-8944, E-ISSN: 2708-8952 Volume 5, Issue 8, P.No. 2402-2426, August 2024 DOI: 10.51594/Estj.V5i8.1363
[36]. Hayashi, Y. (2022). Emerging Trends In Deep Learning For Credit Scoring: A Review. Electronics, 11(19), 3181. Https://Doi.Org/10.3390/Electronics11193181
[37]. Idroes, Ghalieb Mutig & Maulidar, Putri & Marsellindo, Rio & Afjal, Mohd & Hardi, Irsan. (2024). The Impact Of Credit Access On Economic Growth In SEA Countries. Indatu Journal Of Management And Accounting. 2. 96-104. 10.60084/Ijma.V2i2.256.
[38]. Jahanzaib Alvi, Imtiaz Arif, Kehkashan Nizam. (2024). Advancing Financial Resilience: A Systematic Review Of Default Prediction Models And Future Directions In Credit Risk Management. Heliyon, Volume 10, Issue 21, E39770, ISSN 2405-8440. Https://Doi.Org/10.1016/J.Heliyon.2024.E39770.
[39]. Jha, Rahul. (2024). ALGORITHMIC BIAS AND SOCIAL INEQUALITY IN AI DECISION-MAKING SYSTEMS FROM A SOCIOLOGICAL PERSPECTIVE. Shodhkosh: Journal Of Visual And Performing Arts. 5. 10.29121/Shodhkosh.V5.I6.2024.6167.
[40]. John Akwetey Boafo, Maud Avevor And Noble Osei Poku Danzerl. (2025). AI-Powered Credit Risk Assessment In Development Finance: Opportunities And Ethical Challenges In Emerging Markets. World Journal Of Advanced Research And Reviews, 2025, 26(03), 068–074. DOI: Https://Doi.Org/10.30574/Wjarr.2025.26.3.2119
[41]. Julien Kiesse Bahangulu And Louis Owusu-Berko. (2025). Algorithmic Bias, Data Ethics, And Governance: Ensuring Fairness, Transparency And Compliance In AI-Powered Business Analytics Applications World Journal Of Advanced Research And Reviews, 2025, 25(02), 1746-1763. DOI: Https://Doi.Org/10.30574/Wjarr.2025.25.2.0571
[42]. JUMO. (2024). Can AI Solve Financial Inclusion In Africa? JUMO. Retrieved November 11, 2025, From Https://Jumo.World/Can-Ai-Solve-Financial-Inclusion-In-Africa/
[43]. Kagan, J. (2025). FICO (Fair Isaac Corporation). Investopedia. Https://Www.Investopedia.Com/Terms/F/Fico-Fair-Isaac.Asp
[44]. Kang, Zhi & Sin Yin, Teh & Tan, Samuel & Ng, Wei Chien. (2025). Loan Default Prediction Using Machine Learning Algorithms. Journal Of Informatics And Web Engineering. 4. 232-244. 10.33093/Jiwe.2025.4.3.14.
[45]. Kyeong, S., Kim, D., & Shin, J. (2022). Can System Log Data Enhance The Performance Of Credit Scoring?—Evidence From An Internet Bank In Korea. Sustainability, 14(1), 130. Https://Doi.Org/10.3390/Su14010130
[46]. Liz Deichmann. (2025). Access To Credit And Financial Services: A Bridge To Financial Well-Being. Federal Reserve Bank Of St. Louis Https://Www.Stlouisfed.Org/Community-Development/Publications/Access-Credit-Financial-Services-Bridge-Financial-Well-Being
[47]. Marcos R. Machado, Daniel Tianfu Chen, Joerg R. Osterrieder. (2025). An Analytical Approach To Credit Risk Assessment Using Machine Learning Models. Decision Analytics Journal, Volume 16, 100605, ISSN 2772-6622. Https://Doi.Org/10.1016/J.Dajour.2025.100605.
[48]. Martina Mutheu Mulwa And Umar Yahya. (2025). Review Of Digital Lending Models For Financial Inclusion: Challenges, Opportunities, And Way Forward. (2025). European Journal Of Business And Management Research, 10(2), 184-191. Https://Doi.Org/10.24018/Ejbmr.2025.10.2.2211
[49]. Matteo Crosignani, Jonathan Kivell, Daniel Mangrum, Donald Morgan, Ambika Nair, Joelle Scally, And Wilbert Van Der Klaauw. (2025). Financial Inclusion In The United States: Measurement, Determinants, And Recent Developments. Federal Reserve Bank Of New York Economic Policy Review 31, No. 3. Https://Www.Newyorkfed.Org/Medialibrary/Media/Research/Epr/2025/EPR_2025_Financial-Inclusion_Crosignani.Pdf
[50]. Mienye, E., Jere, N., Obaido, G., Mienye, I. D., & Aruleba, K. (2024). Deep Learning In Finance: A Survey Of Applications And Techniques. AI, 5(4), 2066-2091. Https://Doi.Org/10.3390/Ai5040101

[51]. Miracle, Agboola & Shola, Adeyemi & Seun, Odunayo. (2024). THE IMPACT OF MACHINE LEARNING ON CREDIT RISK MODELLING.

[52]. Mokheleli, Tsholofelo & Museba, Tino. (2023). Machine Learning Approach For Credit Score Predictions. Journal Of Information Systems And Informatics. 5. 497-517. 10.51519/Journalisi.V5i2.487.

[53]. Muraina, Ismail & Adesanya, Olayemi & Abam, Solomon. (2023). Data Analytics Evaluation Metrics Essentials: Measuring Model Performance In Classification And Regression.

[54]. Nayak, Saugat. (2022). LEVERAGING NATURAL LANGUAGE PROCESSING (NLP) AND MACHINE LEARNING FOR SENTIMENT ANALYSIS IN FINTECH: ENHANCING CUSTOMER INSIGHTS AND DECISION-MAKING. International Journal Of Applied Engineering And Technology (London). 4. 242-260.

[55]. Nicolas Lainez And Jodi Gardner. (2023). Algorithmic Credit Scoring In Vietnam: A Legal Proposal For Maximizing Benefits And Minimizing Risks. Asian Journal Of Law And Society, Volume 10 , Issue 3 , October 2023 , Pp. 401 - 432. DOI: Https://Doi.Org/10.1017/Als.2023.6

[56]. Nikita Kozodoi. (2024). Fighting Sampling Bias: A Framework For Training And Evaluating Credit Scoring Models. Https://Arxiv.Org/Html/2407.13009v1

[57]. Niquini, F. G. F., Branches, A. M. B., Costa, J. F. C. L., Moreira, G. D. C., Schneider, C. L., Araújo, F. C. D., & Capponi, L. N. (2023). Recursive Feature Elimination And Neural Networks Applied To The Forecast Of Mass And Metallurgical Recoveries In A Brazilian Phosphate Mine. Minerals, 13(6), 748. Https://Doi.Org/10.3390/Min13060748

[58]. Nitisha Aggarwal, Unmesh Shukla, Geetika Jain Saxena, Mukesh Rawat, Anil Singh Bafila, Sanjeev Singh, And Amit Pundir. (2023). Mean Based Relief: An Improved Feature Selection Method Based On Relieff. Applied Intelligence 53, 19, 23004–23028. Https://Doi.Org/10.1007/S10489-023-04662-W

[59]. Nuka, Tambari & Ogunola, Amos. (2024). AI And Machine Learning As Tools For Financial Inclusion: Challenges And Opportunities In Credit Scoring. International Journal Of Science And Research Archive. 13. 1052-1067. 10.30574/Ijsra.2024.13.2.2258.

[60]. Olujimi, P.A., Ade-Ibijola, A. (2023). NLP Techniques For Automating Responses To Customer Queries: A Systematic Review. Discov Artif Intell 3, 20 (2023). Https://Doi.Org/10.1007/S44163-023-00065-5

[61]. Oyewale Oyedokun, Somto Emmanuel Ewim, & Oluwaseun Peter Oyeyemi. (2024). Developing A Conceptual Framework For The Integration Of Natural Language Processing(NLP) To Automate And Optimize AML Compliance Processes, Highlighting Potential Efficiency Gains And Challenges. Computer Science & IT Research Journal P-ISSN: 2709-0043, E-ISSN: 2709-0051 Volume 5, Issue 10, P.2458-2484, October 2024 DOI: 10.51594/Csitrj.V5i10.1675

[62]. Ozanne, Alessio (2024). Black Box Credit Scoring And Data Sharing (November 1, 2024). Proceedings Of The EUROFIDAI-ESSEC Paris December Finance Meeting 2024, Available At SSRN: Https://Ssrn.Com/Abstract=5036281 Or Http://Dx.Doi.Org/10.2139/Ssrn.5036281

[63]. PERC. (2025). The Problem: Credit Invisibility And Its Consequences. Policy & Economic Research Council. Https://Www.Perc.Net/Problem/

[64]. Shi, S., Tse, R., Luo, W. Et Al. (2022). Machine Learning-Driven Credit Risk: A Systemic Review. Neural Comput & Applic 34, 14327–14339 (2022). Https://Doi.Org/10.1007/S00521-022-07472-2

[65]. Shih, D.-H., Wu, T.-W., Shih, P.-Y., Lu, N.-A., & Shih, M.-H. (2022). A Framework Of Global Credit-Scoring Modeling Using Outlier Detection And Machine Learning In A P2P Lending Platform. Mathematics, 10(13), 2282. Https://Doi.Org/10.3390/Math10132282

[66]. Shreya & Harsh Pathak. (2025). Explainable Artificial Intelligence Credit Risk Assessment Using Machine Learning. Https://Arxiv.Org/Html/2506.19383v1

[67]. Shukla, Deepa & Gupta, Sunil. (2024). Feature Engineering Techniques To Enhance Credit Scoring Models. 1-5. 10.1109/ICECIE63774.2024.10815675.

[68]. Song, Mei & Esther, Dorcas. (2022). AI In Behavioral Analysis For Customer Credit Profiling.

[69]. Stan Austin, TEN (2024). How Traditional Credit Scoring Can Be A Barrier For Many Consumers. Federal Reserve Bank Of Kansas City. Https://Www.Kansascityfed.Org/Ten/How-Traditional-Credit-Scoring-Can-Be-A-Barrier-For-Many-Consumers/

[70]. Stephen Onyekachi Obiya. (2024). Leveraging Blockchain And Data Analytics To Enhance Financial Inclusion In Nigeria: A Study Of Blockchain-Based Information System. International Journal Of Research And Scientific Innovation (IJRSI) ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XI Issue X

[71]. Suresh M., Dr.G.Vincent, Dr.C.Vijai, Dr.M.Rajendhiran, M.Com, Ph.D., A.H.Vidhyalakshmi, & Dr Sundarapandiyan Natarajan. (2024). Analyse Customer Behaviour And Sentiment Using Natural Language Processing (NLP) Techniques To Improve Customer Service And Personalize Banking Experiences. Educational Administration: Theory And Practice, 30(5), 8802–8813. Https://Doi.Org/10.53555/Kuey.V30i5.4462

[72]. SWASTIK. (2025). SMOTE For Imbalanced Classification With Python. Https://Www.Analyticsvidhya.Com/Blog/2020/10/Overcoming-Class-Imbalance-Using-Smote-Techniques/

[73]. Techcrunch. (2021). With Over 1.3 Million Users, Nigerian-Based Fintech Fairmoney Wants To Replicate Growth In India. Techcrunch. Retrieved November 11, 2025, From Https://Techcrunch.Com/2021/02/18/With-Over-1-3-Million-Users-Nigerian-Based-Fintech-Fairmoney-Wants-To-Replicate-Growth-In-India

[74]. Trevor J. Bakker, Stefanie Deluca, Eric A. English, Jamie Fogel, Nathaniel Hendren, And Daniel Herbst. (2025). Credit Access In The United States. Https://Www.Census.Gov/Library/Working-Papers/2025/Adrm/CES-WP-25-45.Html

[75]. World Bank. (2025). Financial Inclusion Overview. World Bank. Https://Www.Worldbank.Org/En/Topic/Financialinclusion/Overview

[76]. U.S. Department Of The Treasury. (2024). National Strategy For Financial Inclusion 2022–2026. Https://Home.Treasury.Gov/System/Files/136/NSFI.Pdf

[77]. Umeaduma, Chidimma & Adeniyi, Adedapo. (2025). AI-Powered Credit Scoring Models: Ethical Considerations, Bias Reduction, And Financial Inclusion Strategies. International Journal Of Research Publication And Reviews. 6. 6647-6661. 10.55248/Gengpi.6.0325.12106.

[78]. Y. Zhou. (2022). "Loan Default Prediction Based On Machine Learning Methods," In Proceedings Of The 3rd International. Conference On Big Data Economy And Information Management, BDEIM, Pp. 2-3, 2022

[79]. Yimer, G. (2025). Informal Credit Market: A General Overview. In: The Nexus Between Legal Pluralism And Inclusive Finance. Springer, Cham. Https://Doi.Org/10.1007/978-3-031-71653-9_2

[80]. Zest AI. (N.D.). Underwriting. Retrieved November 11, 2025, From Https://Www.Zest.Ai/Product/Underwriting