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Abstract

Financial inclusion has attracted attention from practitioners, policymakers, and researchers as a strategy for expanding financial access and supporting socioeconomic development among individuals, households, businesses, and economies. It refers to adequate access to affordable financial services, including payments, credit, savings, and insurance. As Kenya pursues Vision 2030 and Agenda 2063, financial inclusion remains central to inclusive growth. This study examined the role of artificial intelligence-driven credit scoring in advancing financial inclusion in Kenya and the importance of balancing innovation with governance safeguards. A systematic review was conducted using peer-reviewed journal articles, reports, and publications from authoritative institutions, including the World Bank and Central Bank of Kenya. The review found that AI-driven credit scoring expands credit assessment beyond conventional credit histories and collateral through alternative data such as mobile-money transactions, utility payments, rental records, and behavioural information. It can improve predictive accuracy, lending efficiency, and access to credit among underserved populations. However, governance challenges remain, including algorithmic bias, discrimination, privacy risks, limited transparency, model reliability concerns, weak accountability, and data protection gaps. The study concludes that the contribution of AI-driven credit scoring to financial inclusion depends on balancing technological innovation with governance safeguards. Financial institutions should implement fairness testing, data-quality controls, privacy protection, cybersecurity measures, and transparent model governance. Regulators, particularly the Central Bank of Kenya, should strengthen adaptive frameworks governing alternative-data use, consumer consent, algorithmic fairness, transparency, accountability, and data protection. Further cross-sectional and longitudinal studies are recommended to assess long-term inclusion outcomes and sustainable AI-enabled credit systems in Kenya.

Keywords: *AI-Driven Credit Scoring, Financial Inclusion, Balancing Innovation, Governance Safeguards, Kenya*

1. Introduction

Financial inclusion has attracted the attention of industry practitioners, policymakers and researchers as a strategy to drive financial access and accelerate socioeconomic development among individuals, households, businesses and the country's economy. As such, financial inclusion refers to the adequate access to affordable financial services such as payments, credit, savings products, and insurance (World Bank, 2024). It is a critical financial for poverty reduction and socioeconomic growth. While financial inclusion is critical driving growth and resilience, over 1.4 billion adults globally remain unbanked (World Bank, 2024). Global account ownership increased from 51 percent in 2011 to 76 percent in 2021 (World Bank, 2024). Despite such encouraging progress, more than a billion people around the world remain financially excluded. An estimated 65 percent of adults in the global low-income economies lack access to even the most basic transaction account.

In Sub-Saharan Africa (SSA), while access to financial services has been rising since early 2010, a substantial size of population remains excluded from the main stream banking system (Jama et al., 2025). It is estimated that an average of 49 percent of adults in SSA own an account, which is a double increase since 2011. When viewed from the perspective of individual economies, nevertheless, there still exist a huge variation in account ownership, ranging from 6 percent in South Sudan to 91 percent in Mauritius (World Bank, 2024). In 16 of the 36 economies surveyed in 2021-2022, well over 50 percent of adults have an account with Senegal (56 percent), Kenya (79 percent), and South Africa (85 percent).

Kenya, is one of countries in Africa and SSA Africa that has met significant progress in advancing financial inclusion. As Kenya seeks to attain Kenya Vision 2030, Agenda 2063, financial inclusion remains very important in Kenya. The Kenya National Financial Inclusion Strategy 2025-2028 (NFIS 2025-2028), seeks to leverage digital transformation and financial literacy to enhance financial inclusion and financial health (CBK, 2025). The Kenya NFIS 2025-2028 aims to improve financial health by deepening the penetration of financial services, enhancing the usage of quality and affordable financial products, and strengthening consumer protection, market conduct, financial literacy and financial capability throughout the nation. The country has witnessed increase in financial inclusion from 26.7 percent in 2016 to 84.8 percent in 2024. Despite this, the level of financial health has been on a downward trajectory falling from 39.6 percent in 2016 to 18.3 percent in 2024 thus exposing the underbelly of the financial exclusion gaps and low financial literacy levels (CBK, 2025).

The full realization of equitable and sustainable development as envisioned in Kenya Vision 2030, depends on inclusive access to quality, affordable, and timely financial products and services that. Vision 2030 identifies financial services as a key enabler for economic and social transformation, emphasizing the need for inclusive financial systems that leave no one behind. Kenya has consistently emerged as a regional and global leader in financial inclusion, driven by rapid technological advancements, innovation led public-private partnerships, and progressive regulatory reforms. The FinAccess Household Survey (2024) shows that 84.8% of Kenyan adults now have access to formal financial services up from 83.7% in 2021, a significant rise from just 26.7% in 2006. This transformation is largely attributed to the widespread adoption of mobile money platforms, the growth of agency banking, digital credit, and SACCOs. Figure 1 shows Financial Inclusion in Kenya 2011-2024.

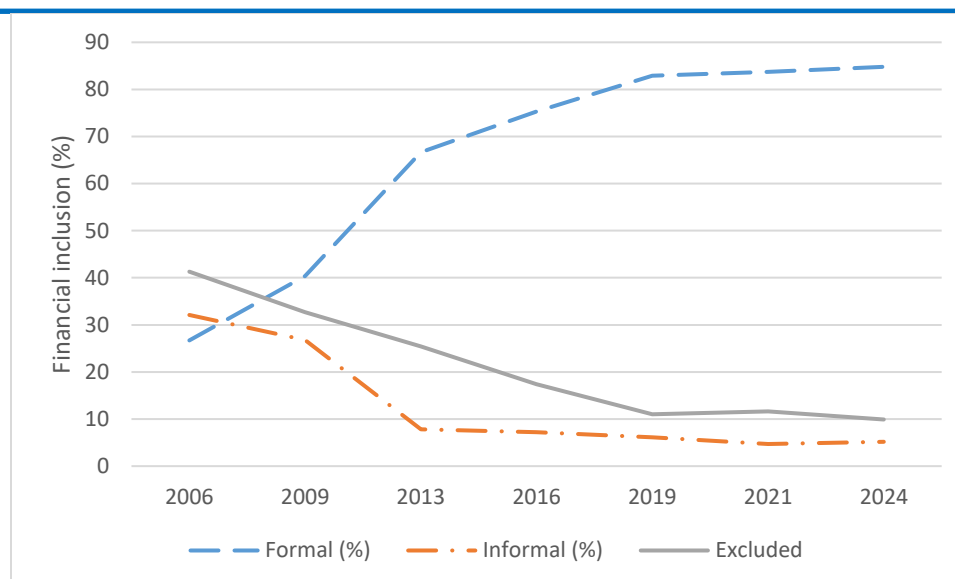


Figure 1: Financial Inclusion in Kenya 2011-2024.

Source: 2024 FinAccess Survey

Kenya experienced a substantial improvement in financial inclusion between 2006 and 2024, reflected in the steady expansion of access to formal financial services and the corresponding decline in financial exclusion. Formal financial inclusion increased from 26.7% in 2006 to 84.8% in 2024, representing an increase of 58.1 percentage points. The most pronounced growth occurred between 2009 and 2013, when formal inclusion rose from 40.4% to 66.7%, followed by continued increases to 75.3% in 2016, 82.9% in 2019, 83.7% in 2021 and 84.8% in 2024. Over the same period, the proportion of the population relying on informal financial services declined substantially from 32.1% to 5.2%, indicating a progressive shift towards formal financial institutions and services. This transformation reflects the increasing integration of Kenyans into the formal financial system and the growing availability and use of accessible financial services.

The improvement in formal financial inclusion was accompanied by a marked reduction in financial exclusion, which declined from 41.3% in 2006 to 9.9% in 2024, a reduction of 31.4 percentage points. The decline was particularly notable between 2006 and 2019, when exclusion fell from 41.3% to 11%, before remaining relatively stable at 11.6% in 2021 and declining further to 9.9% in 2024. However, the persistence of nearly one in ten individuals being financially excluded indicates that access has not yet become universal. Moreover, the slight increase in informal financial participation from 4.7% in 2021 to 5.2% in 2024 suggests that some individuals continue to rely on non-formal mechanisms. The trend demonstrates significant progress in financial inclusion in Kenya, while also highlighting the continuing need for innovative and appropriately governed financial services capable of reaching underserved populations.

The financial systems have been undergoing rapid transformation in the recent years characterized by high level of innovation and technology changes (Gomber, et al. 2018). Adoption of new models, new financial products and new approach of delivery have all been feasible. The innovation and technological progress in financial systems and products has increased speed and

transparency on the operations of the sector. The emergence of Fintech has caused a positive disruption in the financial sector. One of the most identifiable mark left by the adoption of fintech is its cost that is perceived by many as cheap and affordable in the sector (Shahid, & Sheikh, 2021). The rising financial inclusion has been driven by rising use of technologies in finance. This includes digital lending, digital payment, AI-credit scoring, digital financing, and investment (Dias et al., 2026; Li et al., 2024). Other financial technologies driving financial inclusion according to Dias et al. (2026) include e-wallets, mobile banking apps, mobile wallets, electronic banking, agent banking, and online banking transfers. This study narrows to the use of artificial intelligence credit scoring (AI-credit scoring).

Artificial Intelligence (AI)-driven credit scoring systems are rapidly transforming the financial landscape in emerging markets, offering promising solutions to address long-standing challenges of financial exclusion. Traditional credit assessment models, which rely heavily on formal credit histories and collateral, often fail to accommodate low-income individuals, informal workers, and micro-entrepreneurs who lack access to formal banking systems (Essien, 2019). AI-powered credit scoring leverages alternative data sources such as mobile phone usage, digital payment histories, utility bills, social media activity, and psychometric profiles to evaluate creditworthiness. Credit scoring has since emerged as a cornerstone of modern lending practices. By offering a systematic, data-driven approach to evaluating borrower creditworthiness, it has transformed the lending industry (Ayari et al., 2025). At its core, credit scoring quantifies credit risk using applicants' financial behavior and repayment history (Ayari et al., 2025). It ensures objectivity, minimizes human bias, and allows financial institutions to tailor loan terms based on risk profiles, thereby optimizing risk-adjusted returns (Li et al., 2024; Garzozzi-Pincay et al., 2025). The automation of credit risk evaluation not only accelerates loan approval processes enhancing operational efficiency and customer satisfaction, but also strengthens financial stability for both lenders and borrowers.

Against this backdrop, AI-driven credit scoring has emerged as a transformative solution. By leveraging alternative data sources such as mobile phone usage patterns, digital payment records, e-commerce transactions, utility payment histories, and even social media activity, AI-based models are capable of assessing the creditworthiness of individuals previously deemed "unscorable" by conventional methods (Dang, 2025). In many emerging markets, mobile phones and digital payment systems have become deeply integrated into daily life, producing vast amounts of transactional and behavioral data. AI and machine learning (ML) algorithms analyze these data points to detect patterns, predict repayment behaviors, and assign credit scores with far greater flexibility than traditional models. Techniques such as decision trees, neural networks, and ensemble learning enable lenders to process large datasets, continuously refine risk assessments, and extend credit to underserved populations more effectively. The growing adoption of AI-driven credit scoring systems in emerging markets is not only redefining credit access but also reshaping the broader financial inclusion landscape (Gomber et al., 2018; Gozman et al., 2018).

Locally in Kenya, AI-driven credit scoring is rapidly transforming Kenya's financial sector. In March 2025, the Central Bank of Kenya survey on Artificial Intelligence (AI) in the Banking Sector shows that 65% of financial institutions adopted AI for credit risk assessment, making it the most common application (Riskhouse, 2025). A further 83% plan to adopt AI in the future for credit risk assessment. However, Kenya Bankers Association (2026) indicated these emerging technologies are fundamentally changing how banks originate, assess and manage credit, revealing

that nearly 45 per cent of Kenya's commercial banks already use artificial intelligence in credit risk assessment.

The above statistics clearly show that, AI systems are increasingly influencing lending outcomes, offering substantial opportunities to improve financial inclusion and reduce operational costs. While AI-Driven Credit Scoring has gained momentum in driving financial inclusion, it has also attracted concern about its dependability, reliability and data protection and use. Use of AI in credit scoring and risk management continue to introduce complex risks that require responsible fairness, inclusivity and strong risk and governance frameworks. This has brought about balancing innovation with governance safeguards.

2. Theoretical Background

This study is anchored on financial intermediation theory. Financial intermediation theory was advanced in 1950s and 1960s by Gurley and Shaw (1960). According to the theory, financial institutions like banks are important intermediaries between savers and borrowers. The function of financial intermediaries like banks is important to make sure that resources or funds are allocated efficiently (Allen & Santomero, 1997). They help promote efficiency in the markets and lower the cost of doing business and this is vital in the growth and performance of the organisations. Financial intermediation theory facilitates liquidity transformation that is significant to ensure that funds are availed to businesses to enable them to grow and develop (Chant, 1992) Financial intermediation also ensures risk diversification which is important for the stability and sustainability of the business (Bongomin et al., 2022). It also provides expertise that is important in evaluating creditworthiness.

The theory nonetheless has some shortcomings. Financial intermediation is not flexible enough to address the dynamics of the financial sector (Bethune et al., 2021). Over time, the financial sector has undergone substantial changes, creating a need to update theoretical frameworks to better reflect and accommodate the dynamics of modern financial systems. Financial intermediaries also face regulatory challenges which the theory has not considered (Scholtens, B., & Van Wensveen, D. (2003).). The financial regulatory environment is changing daily. The theory should be able to account for this to achieve its objectives effectively. Also, the theory faces fluidity in the financial market (Grassi et al., 2022). The financial market is changing daily, and the theory has failed to cater adequately to this.

The relevance of financial Intermediation Theory to this study lies in its explanation of how financial institutions can improve the allocation of credit and expand access to financial services. Traditionally, credit intermediaries have relied on conventional information, collateral and established credit histories to assess borrowers, potentially excluding individuals and businesses with limited formal financial records. AI-driven credit scoring introduces new approaches to this intermediation process by enabling lenders to analyse large volumes of conventional and alternative data to assess creditworthiness and make lending decisions. In the Kenyan context, such technologies may enhance the efficiency, speed and reach of credit intermediation and potentially extend financial services to previously underserved populations. However, the application of AI also introduces governance concerns relating to data privacy, algorithmic bias, transparency, accountability and consumer protection. Thus, the theory provides a useful foundation for examining how technological innovation can improve the credit intermediation

function while ensuring that expanded access does not compromise fairness and responsible lending.

3. Methodology

In the evaluation of balancing innovation with governance safeguards, with focus to AI-driven credit scoring and financial inclusion in Kenya, this study undertakes a critical review of past studies, their critique, findings and deduction. Research materials that include published journal papers, reports and periodicals were downloaded from Google Scholar. Only data sources from published reviewed journals and authoritative organizations like World Bank, Central Bank of Kenya and Surveys were reviewed. Using systematic review, an in-depth AI-driven credit scoring and financial inclusion was undertaken. It also interrogated the balancing innovation with governance safeguards. Furthermore, an appraisal of available scholarly evidences pertaining AI-driven credit scoring, ethical concerns and the regulatory issues was conducted. One of the major strengths of systematic review methodology is that it provides a comprehensive and transparent basis for understanding an extensive body of existing evidence (Cong-Lem, 2024). It enables researchers to move beyond individual studies and establish broader patterns, relationships, and gaps in knowledge. As such, systematic review thus provides a useful methodology for comparing evidence on the use of AI-driven credit scoring in advancing financial inclusion while debating about the ethical concerns and data governance issues. It further allows the study to identify evidence gaps that require empirical investigation and limited studies are available yet and thus facilitate pooling of knowledge from different sources.

A conclusion was then made based on the review of literature on the significance of AI-driven credit scoring in promoting financial inclusion, practice and policy gaps. Despite these strengths, systematic review methodology has some limitations that should be acknowledged. The findings are dependent on the availability, quality, geographical coverage, and methodological rigour of existing studies. AI-driven credit scoring is an emerging financial technology and as such, country specific materials to Kenan case are limited. This required cautious interpretation when transferring findings from other jurisdictions. Nevertheless, the methodology remains highly relevant in advancing knowledge on AI-driven credit scoring and financial inclusion and the need to balance innovation with governance safeguards. Ayari et al. (2025) used systematic review while studying machine learning powered financial credit scoring.

4. Results

This section presents document results pertaining the use of AI-driven credit scoring in advancing financial inclusion. It also other key concerns raised by researchers, policymakers and industry practitioners.

AI-Driven Credit Scoring and Financial Inclusion

Below is a synthesized empirical-results table focusing specifically on how AI-driven credit scoring promotes financial inclusion, while retaining the study designs, methods and reported findings. Table 1 shows results for AI-driven credit scoring and financial inclusion.

Table 1: AI-Driven Credit Scoring and Financial Inclusion

Author(s)	Study focus	Method/design	Key results
Li et al. (2024)	Effect of AI-enabled credit scoring on financial inclusion among an underserved population	Empirical study involving more than one million underserved customers of a major bank; comparison of an AI-enabled model with the traditional rule-based credit-scoring model	AI-enabled credit scoring increased loan approval rates while simultaneously reducing default rates among underserved borrowers. The findings demonstrate that greater predictive accuracy can support both credit access and responsible lending, thereby enhancing financial inclusion.
Dang (2025)	AI-driven credit scoring, performance, fairness and transparency in alternative-data lending	Comparative empirical analysis using bureau data and alternative indicators such as mobile payments, UPI transaction stability, utility-bill regularity and telecom behavioural data; comparison of ML models with logistic regression	Machine-learning models, particularly gradient boosting and hybrid ensembles, achieved higher predictive accuracy than traditional logistic regression and increased approval rates among thin-file borrowers without a proportional increase in default risk. However, residual disparities across demographic groups remained, demonstrating that increased access does not automatically guarantee equitable inclusion.
Khatri et al. (2025)	AI-driven credit scoring in microfinance and financial inclusion	Mixed-methods approach combining quantitative assessment of AI-based credit models with qualitative analysis of borrower inclusion	AI-based credit scoring increased loan approval among women borrowers by 29.4% and reduced income-based exclusion errors by 24.1% compared with rule-based systems. Predictability of default risk improved by 18.6%.
Marak & Ayyagari (2025)	AI for financial inclusion and sustainable development	Systematic Literature Review using PRISMA; peer-reviewed studies published between 2017 and 2025	The review established that AI has considerable potential to promote financial inclusion and sustainable development.
Vadivelu et al. (2026)	AI-powered credit-scoring models for financial inclusion	Experimental evaluation comparing AI-based credit-scoring models with traditional models using predictive performance measures such as accuracy, precision and recall	AI-based models demonstrated improved accuracy, precision and recall and enhanced the ability to assess individuals without formal credit histories.

Author(s)	Study focus	Method/design	Key results
Yah (2025)	AI-driven credit scoring and financial inclusion in Cameroon	Empirical/conceptual examination of AI-driven credit scoring using broader alternative datasets and machine-learning approaches	AI-driven scoring expanded the assessment of creditworthiness by incorporating utility payments, rental payments, mobile transactions and behavioural data, thereby creating opportunities for underserved individuals with limited or no formal credit histories to access credit.
Mhlanga (2021)	Machine learning, AI and financial inclusion in emerging economies, with focus on South Africa	Literature review and documentary/conceptual analysis	AI and machine learning can strengthen credit-risk assessment by using alternative data to address information asymmetry, adverse selection and moral hazard. Improved assessment of customer behaviour and repayment capacity can enable lenders to extend credit to previously underserved populations.
Oyasiji et al. (2024)	AI-driven credit scoring, fairness, accuracy and regulatory risk	Comparative assessment of AI models and conventional credit-scoring techniques	AI models generally demonstrated higher predictive precision and recall than conventional approaches, indicating potential for improved credit assessment.
Tambari & Amos (2024)	AI and machine learning as tools for financial inclusion in credit scoring	Conceptual/review-based analysis of challenges and opportunities associated with AI and ML in credit scoring	AI and ML provide opportunities to redefine creditworthiness assessment, expand access to credit, improve fairness and reduce disparities affecting underserved populations.
Omambia (2025)	AI and financial performance of the financial services industry in Kenya	Desk review of empirical studies and industry reports published between 2020 and 2025	AI adoption was associated with improved financial-sector performance through better service delivery, expanded financial inclusion and more efficient decision-making.
Ng'ang'a (2026)	AI-driven credit scoring using alternative data in emerging markets	Examination of an AI-powered credit-scoring approach using alternative financial data, including mobile-money usage, financial behaviour and demographic characteristics	Alternative financial data demonstrated potential to improve credit scoring and expand equitable access to credit among underserved populations.
Theuri & Olukuru (2022)	Application of AI in banking	Conceptual/review-based analysis of AI applications in banking	AI can improve banking efficiency through automated customer identification, personalized services, risk assessment, fraud detection, AML and KYC processes.

The existing material indicates that AI-driven credit scoring can promote financial inclusion by improving the identification of creditworthy borrowers who may be excluded by conventional credit-assessment models. Li et al. (2024), for example, found that AI-enabled scoring simultaneously increased approval rates and reduced default rates among an underserved population. Similarly, Dang (2025) found that machine-learning models increased approval rates among thin-file applicants without a proportional increase in default risk, while Khatri et al. (2025) reported a 29.4% increase in loan approval among women borrowers and a 24.1% reduction in income-based exclusion errors. These findings suggest that the ability of AI to incorporate alternative data and identify complex patterns of borrower behaviour can reduce information asymmetry and potentially extend credit to individuals with limited conventional credit histories (Mhlanga, 2021; Ng'ang'a, 2026).

The studies also demonstrate that AI-driven credit scoring can improve the efficiency and predictive performance of lending decisions. Vadivelu et al. (2026) reported improvements in accuracy, precision and recall compared with traditional models, while Oyasiji et al. (2024) found that AI models generally outperformed conventional credit-scoring approaches in predictive precision and recall. The use of alternative information, including mobile transactions, utility payments, rental payments and behavioural data, further expands the information available to lenders when assessing borrowers (Dang, 2025; Yah, 2025). In the Kenyan context, Omambia (2025) similarly associated AI adoption with improved service delivery, decision-making and financial inclusion, while Ng'ang'a (2026) highlights the potential of mobile-money and behavioural data for expanding access to credit in emerging markets.

However, the literature consistently shows that increased credit access through AI does not automatically guarantee equitable financial inclusion. Dang (2025) identified residual disparities across demographic groups despite improvements in predictive performance, while Vadivelu et al. (2026), Yah (2025) and Oyasiji et al. (2024) highlighted concerns relating to algorithmic bias, fairness, data privacy, transparency, model drift and interpretability. Marak and Ayyagari (2025) consequently emphasize the need to combine technological innovation with ethical safeguards and contextual considerations. Thus, the empirical literature supports the potential of AI-driven credit scoring to promote financial inclusion, but it simultaneously establishes the importance of governance safeguards, fairness, transparency, accountability and data protection in ensuring that technological innovation produces inclusive and responsible credit outcomes. Table 2 synthesis issues of concern in the use of AI in advancing financial inclusion.

The results indicates that while AI-driven credit scoring can expand access to finance, its contribution to financial inclusion depends on the extent to which associated governance, ethical, legal and technological risks are effectively managed. The major concerns identified across the studies include algorithmic bias, fairness, data privacy, transparency and explainability, accountability, regulatory compliance, model reliability and data quality. These concerns are particularly important because AI systems may use extensive alternative data to assess individuals who have limited conventional credit histories.

Table 2: *Balancing Innovation with Governance Safeguards*

Author(s)	Study focus	Method	Key governance concern identified	Implications for balancing innovation with governance safeguards
Vadivelu et al. (2026)	AI-powered credit scoring models for financial inclusion	Experimental comparison of AI-based and traditional credit-scoring models	Algorithmic bias, fairness and data privacy	AI improved accuracy, precision and recall and enhanced the identification of borrowers without formal credit histories. However, the study emphasizes that bias and privacy risks require mitigation to ensure ethical implementation. Fairness and privacy safeguards are therefore necessary alongside technological innovation.
Verma et al. (2026)	AI-powered credit scoring amid legal and ethical challenges in India	Comparative/legal and conceptual analysis of AI and conventional credit scoring	Explainability, data privacy, data breaches, accountability and unintended bias	AI offers greater efficiency and predictive capacity but may produce decisions that are difficult to explain. The study calls for fairness, accountability and transparency within the applicable legal and regulatory framework to balance innovation with consumer protection.
Dang (2025)	AI-driven credit scoring, performance, fairness and transparency in alternative-data lending	Empirical analysis using bureau variables and alternative data, including mobile payments, utility-bill regularity and telecom behavioural indicators	Fairness and transparency	ML models improved predictive accuracy and increased approval among thin-file applicants without proportional increases in default. Nevertheless, residual demographic disparities remained, indicating that higher predictive performance alone cannot ensure equitable inclusion. Fairness-aware governance is therefore required.
Khatri et al. (2025)	AI-driven credit scoring in microfinance and inclusive finance	Mixed-methods approach combining quantitative AI-model assessment with qualitative assessment of borrower inclusion	Discrimination and fairness	AI-based scoring increased women's loan approval by 29.4% and reduced income-based exclusion errors by 24.1%, while default-risk prediction improved by 18.6%. The study emphasizes transparent and fairness-sensitive AI models to ensure that increased access translates into responsible inclusion.

Author(s)	Study focus	Method	Key governance concern identified	Implications for balancing innovation with governance safeguards
Marak & Ayyagari (2025)	AI, financial inclusion and sustainable development	Systematic Literature Review using PRISMA	Ethical safeguards and contextual risks	AI has substantial potential for financial inclusion and sustainable development, but its benefits require integration with ethical safeguards, contextual understanding and developmental priorities. Governance should therefore develop alongside technological adoption rather than after implementation. Alternative data can improve access for people with limited formal financial histories. However, interpretability and accountability are needed to strengthen consumer trust and ensure that AI-based decisions comply with regulatory expectations.
Yah (2025)	AI-driven credit scoring and financial inclusion in Cameroon	Examination of AI-based credit assessment using alternative data and machine-learning techniques	Regulatory compliance, algorithmic bias, transparency and accountability	AI generally demonstrates stronger predictive performance, but models may reproduce historical biases or become unreliable because of model drift and overfitting. Fairness-aware algorithms, auditing and explainability mechanisms are therefore important safeguards.
Oyasiji et al. (2024)	Fairness, accuracy and regulatory risk in AI-driven credit scoring	Comparative assessment of AI and traditional credit-scoring models; analysis of regulatory and fairness risks	Algorithmic discrimination, model drift, overfitting and lack of interpretability	AI can reduce processing time and expand access through alternative-data analysis. The study recommends ethical AI guidelines, fairness audits, robust data governance and explainable AI to ensure that innovation supports equitable financial access.
Essien et al. (2019)	AI-driven credit scoring and financial inclusion in emerging markets	Conceptual examination of AI, alternative data and machine-learning techniques	Privacy, algorithmic bias, transparency and regulatory gaps	AI can address limitations of traditional credit assessment and potentially reduce disparities. However, responsible deployment is necessary to ensure that technology does not
Tambari & Amos (2024)	AI and ML as tools for financial inclusion	Review-based analysis of AI and ML opportunities and challenges in credit scoring	Systemic bias and unequal access	

Author(s)	Study focus	Method	Key governance concern identified	Implications for balancing innovation with governance safeguards
Alaba et al. (2026)	AI-powered credit scoring and Nigeria's credit gap	Empirical analysis of alternative data, trust and transparency, awareness/usability and perceived risks	Perceived risk, trust and transparency	reproduce existing inequalities affecting underserved communities. Alternative data, trust and transparency, and awareness/usability had positive and significant effects on financial inclusion, whereas perceived risks had a negative influence. This indicates that public confidence and transparent AI practices are important for translating technological innovation into inclusion.
Omambia (2025)	AI and financial performance of Kenya's financial-services industry	Desk review of empirical studies and industry reports published between 2020 and 2025	Data quality, regulatory compliance and algorithm transparency	AI adoption supports service delivery, financial inclusion and decision-making, but data-quality limitations, regulatory compliance and transparency challenges may constrain its benefits. Kenya therefore requires governance mechanisms that develop alongside AI adoption.
Boafo et al. (2025)	AI-powered credit-risk assessment in development finance	Secondary-data synthesis, case studies and analysis of global policy frameworks	Bias, data privacy, transparency and technological dependency	AI and alternative data can improve predictive accuracy and credit access, but responsible adoption requires inclusive data strategies, explainable AI, regulatory harmonization, local capacity building and digital literacy. AI trained on historical lending data may reproduce or amplify existing inequalities.
Oyasiji et al. (2024)	AI-driven credit scoring, fairness and regulatory risk	Comparative and regulatory-risk analysis	Historical bias, discriminatory outcomes and regulatory compliance	Fairness-aware learning, post-hoc adjustments, auditing and measures such as demographic parity and equalized odds can be considered as mechanisms for monitoring equitable outcomes.

The reviewed studies indicate that balancing innovation with governance safeguards requires treating financial inclusion and responsible AI as complementary objectives rather than competing objectives. AI-driven credit scoring can improve predictive performance, process applications more efficiently and incorporate alternative information that may enable underserved borrowers to enter formal credit markets (Vadivelu et al., 2026; Dang, 2025; Khatri et al., 2025). However, the same technologies can introduce or amplify risks relating to discrimination, privacy, transparency, accountability, regulatory compliance, data quality and model reliability (Essien et al., 2019; Oyasiji et al., 2024; Verma et al., 2026).

For the Kenyan context, the literature therefore points toward a governance framework that allows financial institutions to innovate while establishing safeguards throughout the AI credit-scoring lifecycle. Such safeguards include representative and responsibly sourced data, privacy and security controls, fairness testing and auditing, clear accountability arrangements, consumer redress mechanisms, regulatory oversight and appropriate digital literacy. This approach is consistent with Marak and Ayyagari (2025), who emphasize that the financial-inclusion benefits of AI depend on integrating technological innovation with ethical safeguards and contextual considerations. The central empirical issue for the present study is consequently not simply whether AI can expand credit access, but how its deployment can achieve greater financial inclusion while maintaining fairness, transparency, accountability, privacy and consumer protection.

Practice Gap

The existing empirical literature demonstrates that AI-driven credit scoring has significant potential to promote financial inclusion, particularly by addressing information asymmetry and extending credit assessment beyond conventional credit histories and collateral. Studies by Li et al. (2024), Dang (2025) and Khatri et al. (2025) report increased approval rates among underserved, thin-file and women borrowers, while Vadivelu et al. (2026) and Oyasiji et al. (2024) show improvements in predictive accuracy and lending efficiency. The use of alternative data, including mobile-money transactions, utility payments, rental payments and behavioural information, further enables financial institutions to assess individuals who may previously have been considered difficult to score (Mhlanga, 2021; Yah, 2025; Ng'ang'a, 2026). However, a practice gap remains an issue of concern particularly on ethical issues, data use, data protection and privacy. This creates a dilemma between innovation and governance: expanding the use of AI may enable more accurate and inclusive credit decisions, but poorly governed systems may reproduce discrimination, compromise privacy or create opaque decisions that undermine consumer trust. The significance of AI scoring therefore lies not merely in its capacity to increase the number of people receiving credit, but in its potential to improve the quality, accessibility and efficiency of financial intermediation while reaching populations previously underserved by conventional lending models. This is therefore significant because it addresses this intersection by examining AI-driven credit scoring not only as a technological mechanism for expanding financial access, but also in relation to the governance safeguards required to manage fairness, transparency, accountability, data protection and consumer risks.

Discussion of Results

The empirical evidence demonstrates that AI-driven credit scoring is significant to financial inclusion because it can broaden the basis upon which creditworthiness is assessed, improve lending efficiency and enable financial institutions to reach borrowers who may be excluded by conventional credit-assessment systems. Li et al. (2024) found that AI-enabled scoring simultaneously increased approval rates and reduced default rates among more than one million underserved borrowers. Similarly, Dang (2025) found that machine-learning models increased approval rates among thin-file borrowers without a proportional increase in default risk, while Khatri et al. (2025) reported a 29.4% increase in loan approvals among women borrowers and a 24.1% reduction in income-based exclusion errors. These findings are consistent with Mhlanga (2021) and Ng'ang'a (2026), who show that alternative data can reduce information asymmetry and enable lenders to assess borrowers with limited formal credit histories. Vadivelu et al. (2026) and Oyasiji et al. (2024) further demonstrate that AI models can achieve higher accuracy, precision and recall than conventional approaches, while Yah (2025) shows that mobile transactions, utility payments, rental payments and behavioural information can broaden credit assessment. In Kenya, Omambia (2025) similarly associates AI adoption with improved decision-making, service delivery and financial inclusion.

Nevertheless, the significance of AI-driven credit scoring for financial inclusion should be understood alongside the conditions required for its responsible application. The literature shows that expanding credit access does not automatically result in equitable inclusion. Dang (2025), for instance, identified residual demographic disparities despite improvements in predictive performance, while Oyasiji et al. (2024) highlighted algorithmic bias, model reliability and interpretability concerns. Similarly, Vadivelu et al. (2026) identified fairness and data privacy as important challenges, and Marak and Ayyagari (2025) argue that the contribution of AI to financial inclusion depends on integrating technological innovation with ethical safeguards and contextual considerations. The findings of Tambari and Amos (2024) and Theuri and Olukuru (2022) further indicate that AI can improve financial-service efficiency and reduce barriers to access, but its benefits depend on appropriate implementation. Thus, AI-driven credit scoring is significant because it provides an opportunity to address limitations of traditional credit assessment and extend financial services to underserved populations; however, fairness, transparency, data protection, accountability and effective governance remain essential to ensuring that increased technological access translates into sustainable and equitable financial inclusion.

Balancing Innovation with Governance Safeguards

While AI-driven credit scoring has been found critical in advancing financial inclusion, there remains pertinent issues of concerns demanding the need of balancing innovation with governance safeguards. Empirical evidence shows that AI-based models can increase credit approval, improve predictive accuracy and reduce some forms of exclusion among underserved populations (Li et al., 2024; Dang, 2025; Khatri et al., 2025; Vadivelu et al., 2026). In Kenya, the growing application of AI in financial services similarly presents opportunities to improve decision-making, service delivery and financial access (Omambia, 2025). However, expanding AI adoption without corresponding governance safeguards may undermine the very inclusion it seeks to promote. Algorithmic bias can reproduce historical inequalities, while extensive use of alternative data raises concerns about privacy, data protection and the potential misuse of personal information.

Moreover, opaque algorithms may make it difficult for borrowers to understand or challenge credit decisions.

The practice gap therefore lies not simply in whether AI can expand access to credit, but in how financial institutions can deploy AI-driven credit scoring in a manner that simultaneously promotes inclusion and protects consumers. Existing studies provide evidence of improved credit access and predictive performance, but also identify persistent concerns relating to fairness, transparency, accountability, data quality, privacy, regulatory compliance and model reliability (Dang, 2025; Marak & Ayyagari, 2025; Boafo et al., 2025). This creates a practical need for governance mechanisms that operate throughout the AI credit-scoring lifecycle, including responsible data collection and use, privacy and security controls, fairness testing, model validation and monitoring, independent auditing, accountability and effective consumer redress. Such safeguards are particularly important, where AI-enabled financial services are developing within an evolving digital financial ecosystem (Omambia, 2025).

5. Implication to practice, policy and research

The use of AI scoring in advancing financial inclusion contributes to financial products and services. Financial institutions in Kenya should integrate AI-driven credit scoring into lending processes while embedding governance safeguards throughout the AI lifecycle. The evidence that AI can improve credit approval, predictive accuracy and access among underserved borrowers implies that banks, SACCOs, microfinance institutions and fintech firms should responsibly incorporate alternative data such as mobile-money transactions, utility payments and repayment behaviour to assess borrowers with limited formal credit histories. However, institutions should complement this innovation with regular bias and fairness assessments, data-quality controls, privacy and security measures. These practices would enable institutions to benefit from the efficiency and predictive capabilities of AI while reducing risks associated with discrimination, opaque decisions, inappropriate data use and model instability.

To policy, the findings imply a need for a clear, adaptive and risk-sensitive governance framework for AI-driven credit scoring in Kenya that promotes innovation while protecting consumers and supporting equitable financial inclusion. Policymakers and regulators particularly the CBK need to establish requirements for responsible collection and use of alternative data, consumer consent, data protection, algorithmic fairness, and transparency. Regulatory frameworks should also clarify institutional accountability where automated credit decisions result in errors or discriminatory outcomes and provide effective mechanisms through which consumers can obtain explanations and challenge adverse decisions. These measures are consistent with the literature emphasizing fairness, accountability, transparency, regulatory harmonization and data governance as conditions for responsible AI deployment (Verma et al., 2026; Marak & Ayyagari, 2025; Boafo et al., 2025).

With focus to implication to research, the findings also highlight the need for further Kenya-specific empirical research examining the relationship between AI-driven credit scoring, financial inclusion and governance safeguards. Existing literature provides evidence that AI can improve credit access and predictive performance, but much of the available evidence originates from other emerging markets or relies on conceptual, review-based and secondary-data approaches. Future studies should therefore employ primary and longitudinal data from Kenyan financial institutions to examine whether AI-based scoring actually expands financial access considering is an emerging technology in Kenya.

6. Conclusion

AI-driven credit scoring has significant potential to advance financial inclusion by transforming how financial institutions assess creditworthiness and extending access to borrowers who may be underserved by conventional credit-assessment models. The use of alternative data, including mobile-money transactions, utility payments, rental records and behavioural information, enables lenders to assess individuals with limited or no formal credit histories. AI-based scoring can increase loan approval, improve predictive accuracy and reduce some forms of exclusion, particularly among thin-file and underserved borrowers. Thus, AI-driven credit scoring can contribute to a more accessible and responsive financial system by reducing information asymmetry and enabling financial institutions to serve populations previously constrained by traditional credit-assessment requirements.

Despite its potential, the contribution of AI-driven credit scoring to financial inclusion depends on balancing technological innovation with effective governance safeguards. Greater use of alternative data and automated decision-making can create risks relating to algorithmic bias, discrimination, privacy, data protection, transparency, explainability, accountability, model reliability and regulatory compliance. Evidence that improved credit access can coexist with residual demographic disparities demonstrates that predictive accuracy alone does not guarantee equitable financial inclusion. Therefore, adoption of AI-driven credit scoring in Kenya should be accompanied by responsible data governance, fairness testing, model monitoring, consumer protection and effective redress mechanisms. Sustainable financial inclusion requires technological innovation to operate alongside ethical and institutional safeguards.

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