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(Review Article)

AI-powered credit risk assessment in development finance: Opportunities and ethical challenges in emerging markets

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Abstract

This discussion paper critically reviews the use of artificial intelligence (AI) in credit risk assessment in development finance institutions (DFIs) in emerging markets. The main goal is to assess the opportunities and ethical challenges of AI driven models for financial inclusion. Using secondary data synthesis, case studies and global policy frameworks, the paper examines how machine learning and alternative data sources can improve predictive accuracy, increase credit access and improve DFI operations. It also points out systemic risks such as algorithmic bias, data privacy violation, lack of transparency and technological dependency. The study suggests that responsible AI adoption requires inclusive data strategies, explainable AI frameworks, regulatory harmonization, local capacity building and improved digital literacy. The paper presents a roadmap for using AI as a tool to create equitable and resilient financial ecosystems in low- and middle-income countries by aligning AI deployment with Sustainable Development Goals and ethical governance.

Keywords: Artificial Intelligence; Credit Risk Assessment; Development Finance Institutions; Financial Inclusion; Emerging Markets

1. Introduction

Globally, more than 1.4 billion adults remain unbanked, limiting their access to financial services and constraining economic mobility [15]. Development finance institutions (DFIs) seek to address this gap by promoting inclusive financial systems. Yet, conventional credit risk models often reliant on formal financial histories continue to exclude large segments of the population, particularly in Sub-Saharan Africa and South Asia.

Artificial intelligence (AI) offers a new approach. By leveraging alternative data sources, such as mobile payment patterns, e-commerce transactions, utility bills, and social media activity, AI enables lenders to assess creditworthiness beyond traditional metrics. Using advanced techniques like gradient boosting, neural networks, and natural language processing, DFIs can generate dynamic credit profiles and unlock capital for underserved groups, including informal workers, women, and rural entrepreneurs. These advances support global development priorities, notably SDGs 1 (No Poverty), 5 (Gender Equality), 8 (Decent Work and Economic Growth), and 10 (Reduced Inequalities).

However, the integration of AI into credit systems also raises notable ethical and structural concerns. Algorithmic bias, opaque decision-making processes, privacy risks, and weak data governance frameworks may undermine trust and exacerbate existing inequalities, especially in regions where regulatory oversight is still evolving. Furthermore, heavy reliance on foreign AI platforms introduces issues of data sovereignty and geopolitical vulnerability.

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This article explores both the promise and the risks of AI-powered credit risk assessment. It offers a roadmap for responsible adoption that supports the broader goals of sustainable development, inclusion, and digital sovereignty in emerging markets.

2. AI-Powered Credit Risk Assessment presents several opportunities such as:

2.1. Enhanced Predictive Power

Artificial intelligence (AI), specifically machine learning (ML), is transforming credit scoring by uncovering patterns in unstructured and alternative data that traditional models cannot capture. In many emerging markets, where formal credit bureaus cover less than 20% of the population [10], access to conventional financial data remains limited. ML models help fill this gap by analyzing diverse data streams, including mobile usage patterns, e-commerce transactions, geolocation data, and social media behavior. These insights allow lenders to build detailed credit profiles for "thin file" or unbanked individuals, significantly expanding access to credit.

Evidence suggests that ML-based models, which detect non-linear relationships in alternative data, improve default prediction accuracy by 15–20% compared to standard logistic regression techniques [3]. This predictive strength boosts lender confidence, enabling DFIs to extend credit to higher-risk populations while managing portfolio risk more effectively.

Further support comes from the Bank for International Settlements (BIS), which noted in a 2020 study that ML-driven credit scoring is reshaping lending ecosystems in emerging economies (Cornelli et al., 2020 [7]). According to the BIS, these models have enabled platforms to reach millions previously excluded from formal financial systems, especially in regions with limited credit bureau coverage such as Sub-Saharan Africa. Applications range from microfinance to peer-to-peer lending, highlighting the versatility and impact of ML in promoting inclusive finance.

2.2. Advancing Financial Inclusion

Artificial intelligence (AI) holds significant promise in expanding financial inclusion by enabling credit access for underserved populations. Using alternative data, such as mobile phone usage, e-commerce activity, and geolocation, development finance institutions (DFIs) can evaluate creditworthiness beyond formal financial histories. This capability is particularly valuable for reaching informal sector workers, rural entrepreneurs, women, and youth, who are often excluded from traditional banking systems. These efforts directly support Sustainable Development Goals (SDGs) 1 (No Poverty) and 5 (Gender Equality), promoting economic empowerment and reducing structural inequalities.

Several fintech platforms have demonstrated the practical application of AI in inclusive lending. Tala (Kenya) and Branch (Nigeria), for instance, use AI-driven models to analyze smartphone data, including call logs, app usage, and transaction history. Tala alone has disbursed over $2 billion in microloans to more than six million customers, using AI to assess creditworthiness among unbanked individuals [13]. In India, Aye Finance employs machine learning to evaluate transaction data from small business owners, facilitating access to credit for micro-entrepreneurs previously considered "unbankable" by conventional financial institutions [7].

These examples highlight AI's capacity to unlock capital for marginalized groups and drive inclusive economic growth. In doing so, they also contribute to SDG 8 (Decent Work and Economic Growth), by enabling entrepreneurship and expanding formal economic participation.

2.3. Real-Time Risk Management

Emerging markets are especially susceptible to external shocks. Climate variability, economic downturns, and geopolitical instability all pose ongoing threats to financial stability. Artificial intelligence (AI) provides development finance institutions (DFIs) with advanced tools to manage these risks more proactively. By applying machine learning (ML) models, DFIs can monitor credit portfolios in real-time and identify early signals of borrower distress or broader financial disruptions.

For example, AI-driven stress testing can simulate the effects of climate-related events on agricultural borrowers, enabling lenders to adjust credit strategies before defaults occur (IMF, 2022). Risk models typically integrate satellite imagery, rainfall data, and macroeconomic indicators to produce timely and detailed assessments.

The Bank for International Settlements (BIS) emphasizes the growing role of real-time analytics in fintech credit platforms within emerging economies, particularly where traditional risk models are inadequate [6]. In Kenya, Apollo

Agriculture uses predictive models to revise credit terms for farmers impacted by shifting weather patterns, contributing to Sustainable Development Goal (SDG) 13, focused on climate action [9].

Beyond enhanced accuracy, ML-based systems continuously update borrower profiles as new information becomes available. This level of adaptability allows DFIs to sustain lending activities amid volatility while advancing SDG 1 by preserving access to credit and protecting livelihoods.

2.4. Streamlined Operations and Cost Efficiency

Artificial intelligence (AI) significantly enhances operational efficiency for development finance institutions (DFIs) by automating labor-intensive processes such as loan underwriting, document verification, customer identification (KYC), and fraud detection. These improvements reduce both processing time and operational costs. In document verification, natural language processing (NLP) extracts and validates information from unstructured sources, including handwritten contracts, thereby reducing manual errors. In fraud detection, AI models analyze behavioral patterns, such as irregular transaction frequencies or geolocation inconsistencies, to identify potential misconduct with high precision.

A McKinsey report estimates that AI-powered automation can reduce loan processing times by 20 to 60 percent and cut operating costs by up to 20 percent for financial institutions [11]. In Kenya, M-Pesa applies AI to optimize digital lending workflows, while Zenith Bank in Nigeria uses AI for fraud detection, achieving significant improvements in fraud reduction in line with global benchmarks [12].

For DFIs, such efficiency translates into greater scalability, enabling them to reach a broader borrower base without compromising due diligence. AI-powered systems that analyze behavioral anomalies also reinforce institutional integrity, particularly in regions where financial misconduct is more prevalent. The African Development Bank, for instance, has implemented AI tools to streamline microloan approvals, cutting underwriting time from weeks to days and expanding access for rural entrepreneurs [1]. In this way, AI-driven efficiency advances SDG 9 by reinforcing innovation and infrastructure within the financial sector.

3. Ethical Challenges and Systemic Risks

AI-powered credit risk assessment encounters considerable ethical, operational, and systemic challenges that need to be addressed to ensure fair outcomes:

3.1. Algorithmic Bias and Inequity

The effectiveness and fairness of AI systems depend heavily on the quality and inclusiveness of the data used in training. When underlying datasets reflect historical disparities in credit access, those inequities are often reproduced by the model. In many lending environments, women, rural populations, and low-income borrowers have been underrepresented, resulting in biased outcomes that disadvantage these groups.

In Sub-Saharan Africa, for example, women have experienced loan approval rates that are 15 to 20 percent lower than their male counterparts, reflecting structural bias embedded in traditional credit scoring frameworks [4]. AI tools trained on such data risk perpetuating these patterns. In Kenya, rural women entrepreneurs remain underserved by fintech platforms due to limited digital access and credit models that tend to favor urban male users [4, 5].

These challenges highlight the need for more representative and equity-oriented data strategies. Without deliberate efforts to account for demographic variation and structural exclusion, AI-powered credit scoring may widen existing gaps in financial inclusion rather than close them.

3.2. Lack of Transparency and Accountability

Many AI-driven credit assessment models operate without clear mechanisms for transparency or explanation. These systems often rely on historical data that may contain embedded biases. When such biases go unexamined, they can be reinforced under the appearance of objectivity. The risks are especially pronounced in environments with limited regulatory oversight or weak legal recourse.

In numerous emerging markets, where institutional frameworks are still developing, borrowers often have no effective means to question or understand the basis of credit decisions generated by complex algorithms. This lack of clarity not only deepens existing vulnerabilities but also erodes confidence in digital financial services.

There is, however, increasing regulatory momentum aimed at addressing these concerns. Frameworks such as the European Union's General Data Protection Regulation (GDPR) and emerging data protection laws in countries like Kenya and Nigeria are beginning to enforce greater transparency and accountability in automated decision-making. These developments highlight the urgent need for AI systems in credit scoring to be explainable and auditable not only to meet compliance standards but also to foster trust and promote fair treatment across diverse borrower populations.

3.3. Privacy and Data Governance

The growing use of alternative data in AI-driven credit assessment raises significant privacy concerns. Sensitive information such as geolocation, mobile phone usage, and social media behavior can be subject to misuse, especially in jurisdictions with weak regulatory safeguards. While frameworks like the European Union's General Data Protection Regulation (GDPR) and Nigeria's Nigeria Data Protection Regulation (NDPR) aim to strengthen privacy protections, many emerging markets still lack robust enforcement mechanisms and comprehensive legal frameworks.

In low-income countries, limited digital literacy further complicates matters. Many mobile users remain unaware of how their data is collected, processed, or shared, making informed consent difficult to obtain [8]. This environment increases the risk of privacy violations and unauthorized data sharing, particularly among fintech lenders. When borrower information is mishandled or shared without consent, it undermines trust in digital financial services and poses long-term challenges to financial inclusion efforts.

3.4. Technological Dependency and Sovereignty

The widespread deployment of AI systems developed by foreign technology firms introduces critical concerns around digital dependency and sovereignty. Over-reliance on external platforms can compromise domestic control over financial infrastructure, making development finance institutions (DFIs) vulnerable to external geopolitical or commercial pressures [14]. Sudden changes in licensing terms, data access policies, or platform availability may disrupt operations and limit strategic autonomy.

In Africa, many DFIs and fintech companies remain dependent on foreign-built AI and data systems. This reliance increases exposure to geopolitical risk and underscores the urgent need for regionally governed, context-specific technological frameworks [2, 14]. Developing local capacity and infrastructure is therefore essential for reducing systemic vulnerability and promoting long-term sustainability.

Moreover, the high upfront costs associated with AI implementation can place a significant burden on institutional budgets in low-resource settings. Without adequate investment in local talent, infrastructure, and regulatory frameworks, DFIs risk reinforcing external dependency while limiting their ability to innovate independently.

4. Strategic recommendations

While the challenges associated with AI in credit scoring are significant, the technology's potential to transform financial inclusion in emerging markets remains compelling. Machine learning (ML) models, when grounded in robust predictive methodologies and supported by inclusive data practices, offer powerful tools for expanding access to credit and strengthening financial resilience. With the right safeguards, these systems can help development finance institutions (DFIs) meet global development priorities and close longstanding gaps in financial access.

Realizing this potential will require coordinated action. Policymakers, fintech innovators, and researchers must work collaboratively to develop and implement comprehensive strategies that ensure the ethical, transparent, and equitable use of AI in financial services. This includes addressing concerns related to bias, transparency, data governance, and technological sovereignty. Strategic investments in infrastructure, regulation, and capacity-building will be essential to ensure that AI-driven credit systems deliver sustainable and inclusive benefits for underserved populations.

4.1. Develop Inclusive and Transparent Data Frameworks

Addressing bias in AI-driven credit assessment begins with the use of diverse and representative datasets that reflect the realities of marginalized populations. Ensuring fairness requires regular audits using well-defined metrics, alongside the adoption of fairness-aware algorithms capable of delivering equitable outcomes across demographic and socio-economic lines. Development finance institutions (DFIs) should work closely with local stakeholders to co-design inclusive credit models that are contextually relevant and socially responsive. Such efforts directly advance Sustainable Development Goal 5 (Gender Equality) by promoting broader access to financial services.

Transparency is equally critical. Stakeholders should adopt explainable AI (XAI) frameworks to improve model interpretability, thereby strengthening accountability and fostering trust among borrowers, regulators, and the public.

In parallel, emerging markets must prioritize technological sovereignty by investing in local AI development and open-source infrastructure. DFIs can play a leading role by supporting regional research initiatives and fostering innovation ecosystems tailored to their operational contexts. India's AI4Bharat initiative, which creates open-source AI tools for financial inclusion, serves as a compelling example of how local development can drive self-reliance. These investments enhance institutional resilience and support Sustainable Development Goal 9 (Industry, Innovation, and Infrastructure).

4.2. Strengthen AI Governance and Regulation Harmonization

Establishing harmonized standards for AI-driven credit assessment is essential to balance innovation with consumer protection. Development finance institutions (DFIs), regulators, and policymakers must collaborate across national and regional levels to ensure that legal frameworks keep pace with technological change. Clear, coordinated guidelines will support scalability while addressing ethical risks associated with data use, model transparency, and algorithmic accountability.

Compliance with emerging regulatory instruments, such as the European Union's AI Act, reinforces the need for transparency and explainability. This requires DFIs to invest in explainable AI (XAI) frameworks such as SHAP (SHapley Additive exPlanations) which provide interpretable insights into model decisions. These tools not only enhance regulatory compliance but also allow borrowers to understand and challenge adverse credit decisions, thereby reinforcing procedural fairness.

Effective deployment of AI in credit risk assessment requires attention not only to model design but also to its lifecycle management. Machine learning systems evolve over time and often require regular retraining to remain accurate as borrower behavior and macroeconomic conditions change. Without adequate monitoring, AI models risk performance degradation or the reinforcement of outdated biases. DFIs should therefore establish governance mechanisms such as audit trails, bias dashboards, and model validation protocols to ensure continuous fairness, reliability, and accountability. Embedding these practices into operational workflows is essential for maintaining trust and minimizing systemic risk.

Additional mechanisms, such as regulatory sandboxes, offer a controlled environment for testing AI innovations while preserving oversight. Ethical guidelines, modeled on continental instruments like the African Union's Malabo Convention, can further guide the development of interoperable governance systems across jurisdictions.

To ensure long-term alignment with human rights and development priorities, stakeholders should also consider establishing independent ethical review boards. These bodies can oversee implementation, monitor compliance, and promote transparency, all of which are critical for building trust and legitimacy in AI-based credit systems.

4.3. Support Local Capacity and Infrastructure

Building sustainable and inclusive AI ecosystems in emerging markets requires targeted investments in local capacity and infrastructure. Governments and development finance institutions (DFIs) should partner with local fintech firms, technology providers, universities, and development agencies to share resources and expertise. Such collaborations can help establish data ecosystems that reflect diverse socio-economic realities, including informal income sources and community-based financial behaviors.

Effective public-private partnerships reduce dependence on foreign platforms, enhance data sovereignty, and lower implementation costs. By accelerating innovation and promoting context-sensitive design, these partnerships also support the development of ethical data collection practices and more inclusive financial technologies.

Targeted support mechanisms, including grants, incubators, and university-led research programs can nurture homegrown AI solutions tailored to local challenges. India's regulatory sandbox, which has successfully stimulated fintech innovation, offers a valuable model that can be adapted in other regions. Additionally, capacity-building initiatives for policymakers, regulators, and technologists can empower domestic stakeholders to take an active role in shaping AI adoption and governance.

4.4. Enhance Digital and Financial Literacy

Widespread adoption of AI in financial services must be accompanied by efforts to improve digital and financial literacy. Empowering individuals to navigate automated credit systems requires comprehensive education initiatives that go beyond basic financial knowledge. These programs should include training on digital rights, data privacy, and the implications of algorithmic decision-making.

Kenya's national digital literacy campaigns provide a useful reference point. By increasing public understanding of mobile banking platforms, these initiatives have contributed to greater consumer engagement and improved financial inclusion outcomes. Similar efforts in other emerging markets could play a pivotal role in bridging the knowledge gap between technology providers and users.

Ultimately, enhancing digital and financial literacy not only protects consumers but also strengthens the broader ecosystem. Informed users are more likely to trust AI-enabled systems, while institutions benefit from improved operational efficiency and reduced risk, both of which are essential for scaling financial inclusion sustainably and ethically.

5. Conclusion

The future of AI in development finance hinges on a collective commitment to ethical innovation and inclusive governance. Building responsible AI systems will require collaboration among technologists, policymakers, civil society actors, and international institutions. Together, these stakeholders can foster regulatory alignment, promote accountability, and ensure that AI technologies are adapted to local contexts.

Emerging tools including explainable AI (XAI), decentralized identity frameworks, and open-source platforms offer significant potential to broaden access to credit while managing systemic risks. However, realizing this potential depends on prioritizing justice, sustainability, and inclusivity at every stage of design and implementation.

By embedding these principles into AI deployment strategies, development finance institutions can position artificial intelligence not as a disruptive force, but as a catalyst for building resilient, equitable, and future-ready financial systems across emerging markets.

Policy and Practice Implications

This article contributes to the growing discourse on responsible AI by bridging technical innovation with development finance realities in emerging markets. By integrating empirical case studies, ethical analysis, and policy recommendations, it outlines a practical framework for AI deployment that prioritizes inclusion, transparency, and local ownership. As development finance institutions increasingly adopt data-driven tools, aligning technological progress with social equity will be essential. The recommendations offered here provide a roadmap not only for mitigating risk but also for harnessing AI's potential as a catalyst for resilient and just financial ecosystems.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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