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AI-Driven Credit Assessment and SME Access to Finance in Africa: Opportunities, Risks and Regulatory Responses.

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ABSTRACT

Small and medium-sized enterprises (SMEs) contribute substantially to employment, innovation and economic diversification in Africa, yet many remain excluded from formal finance because they lack collateral, audited accounts and established credit histories. This study examined the opportunities, risks and regulatory responses associated with AI-driven credit assessment and SME finance in Africa through an integrative systematic review of peer-reviewed studies, regulatory documents and institutional reports published mainly between 2021 and 2026. A PRISMA-informed selection process and thematic analysis organised the evidence around inclusion, alternative data, efficiency, bias, privacy, cybersecurity and consumer protection. The findings indicate that machine learning can reduce information asymmetry, underwriting costs and processing time for thin-file SMEs. Outcomes nevertheless differ by country. Kenya combines mature mobile finance with direct digital-credit rules; Nigeria has market scale but fragmented oversight; South Africa has stronger financial and data-protection institutions; Ghana is formalising digital-credit supervision; and Rwanda has an explicit national AI policy but a smaller credit market. Current models remain vulnerable in low-data environments because sparse, unrepresentative and unstable records weaken calibration, fairness and transferability. The study proposes an integrated framework linking AI capability, data quality, financing outcomes, technological risks, institutional conditions and regulatory safeguards. Responsible adoption requires locally validated models, measurable subgroup fairness tests, understandable adverse-decision explanations, meaningful human review, cybersecurity controls and coordinated cross-border supervision.

Keywords: Artificial Intelligence; Credit Assessment; SME Finance; Alternative Credit Data; Financial Inclusion; Financial Regulation

INTRODUCTION

Background to the Study

Small and medium-sized enterprises (SMEs) are central to employment creation, innovation, economic diversification and inclusive growth. Their relatively low entry requirements allow them to absorb labour, serve local markets and support value chains that larger firms may not reach. In Africa, however, their contribution remains constrained by limited access to appropriate and affordable finance. The African Development Bank (AfDB, 2021) identifies finance as a major constraint on enterprise development, with the financing shortfall particularly severe among micro, small and medium-sized enterprises.

Globally, SME financing difficulties arise partly from information asymmetry. Lenders possess less reliable information about small firms than about large corporations, while SME owners know more about their businesses and repayment capacity than prospective financiers. This imbalance increases adverse-selection and monitoring risks, encouraging lenders to demand collateral, audited financial statements, formal credit histories and extensive documentation. Many SMEs, especially young and informal enterprises in developing economies, cannot satisfy these requirements. Conventional credit assessment can therefore reject potentially viable firms because they lack documented financial histories rather than because their businesses are uncreditworthy. The resulting credit rationing limits investment, productivity and business growth.

Digital finance has begun to alter this lending environment. Mobile money, electronic payments, e-commerce and digital banking generate transaction records that can supplement conventional credit information. In Sub-Saharan Africa, 55% of adults held an account in 2021, while 7% borrowed through a mobile-money account, indicating the growing relevance of digital financial channels (Demirgüç-Kunt et al., 2022). Fintech lenders increasingly analyse cash-flow records, mobile-wallet transactions, utility payments, online sales and other digital footprints to evaluate borrowers lacking formal credit histories. The World Bank (2022) observes that digital platforms can reduce transaction costs and broaden responsible SME finance by processing larger and more varied datasets than conventional underwriting permits.

Artificial intelligence (AI) extends this development through machine learning, predictive analytics, natural-language processing and automated document analysis. These technologies can identify complex relationships between borrower characteristics and default risk, automate verification and update risk estimates as new information becomes available. Digital-footprint variables have demonstrated predictive value comparable to credit-bureau scores and can complement rather than merely replace traditional information (Berg et al., 2020). A systematic review by Sanga and Aziakpono (2023) similarly finds that fintech, big-data analytics and AI can ease SME financing constraints by improving credit assessment, lowering information costs and widening lenders' reach.

These benefits are particularly relevant in Africa, where many enterprises operate outside comprehensive credit-reporting systems but increasingly leave digital transaction trails. AI-driven assessment may identify creditworthy, thin-file SMEs, shorten processing time, reduce collateral dependence, improve default prediction and support risk-based loan pricing. Yet greater predictive capability does not guarantee fair inclusion. Algorithms trained on incomplete or historically biased data may reproduce existing disadvantages or use location, gender, device type and digital activity as proxies for protected or vulnerable characteristics. Machine learning may improve overall prediction while distributing its benefits unevenly across borrower groups (Fuster et al., 2022). Extensive alternative-data use also raises concerns about consent, privacy, cybersecurity, opaque decisions, identity theft and borrowers' ability to challenge inaccurate assessments.

Research Problem

AI-driven credit assessment presents a central contradiction. It can reduce the informational barriers that exclude African SMEs from formal lending, but it can also automate and intensify exclusion. Many African SMEs have limited credit histories, fragmented financial records and few assets acceptable as collateral. Lenders consequently incur high screening and monitoring costs, while borrowers face delayed decisions, small loan amounts or outright rejection.

AI models can address these weaknesses only when their data are accurate, representative and lawfully obtained. Models trained predominantly on formal, urban or digitally active businesses may misclassify rural, informal, women-owned and newly established enterprises. Personal and behavioural information may also be collected without meaningful consent or a clear connection to creditworthiness. When automated systems operate as "black boxes," rejected applicants may receive no understandable explanation or effective opportunity for human review. Aggarwal (2021) argues that algorithmic credit scoring creates tensions among allocative efficiency, distributional fairness and privacy that existing credit and data-protection arrangements may not resolve adequately.

Cyberattacks, manipulated records, identity theft and third-party technology failures further threaten borrowers and lenders. These risks are aggravated by uneven regulatory capacity and fragmented responsibility among central banks, consumer-protection bodies, cybersecurity agencies and data-protection authorities. Although several African countries have enacted data-protection legislation, coverage and enforcement of profiling and automated decision-making remain inconsistent. South Africa's experience, for example, indicates that general financial and data rules may require clearer AI-specific standards on accountability, cybersecurity and inclusion

(Makore, 2024). The unresolved problem is therefore whether AI credit assessment can expand SME finance without replacing traditional information barriers with data-driven discrimination, intrusive surveillance and weakly contestable decisions.

Research Gap and Motivation

Four connected gaps justify this study. Conceptually, existing research often treats fintech, digital lending and financial inclusion separately; fewer studies integrate AI credit assessment, SME financing outcomes, technological risks and regulatory safeguards within one analytical framework. Contextually, much of the established evidence comes from developed economies and large digital-credit markets whose credit infrastructure, data quality and supervisory capacity differ from African conditions.

Empirically, African evidence remains dispersed across studies of mobile lending, alternative data, fintech, credit scoring, cybersecurity and data protection. Even recent reviews confirm that the SME-fintech literature remains fragmented across technologies, jurisdictions and financing channels (Sanga & Aziakpono, 2023). The regulatory literature also concentrates more heavily on predictive performance than on explainability, privacy, model validation, consumer redress and institutional accountability. Although AI may support the inclusion of underserved groups in countries such as Nigeria, product design and data practices can retain gendered and structural biases (Omotubora, 2024). This study responds by providing an Africa-centred synthesis that evaluates financing opportunities together with their risks and regulatory conditions.

Research Questions

The study addresses the following questions:

1. How is AI-driven credit assessment applied to SME lending in Africa?
2. Through what channels does it improve SME access to finance?
3. What risks arise from alternative credit data and automated credit decisions?
4. How adequate are existing African regulatory responses?
5. What safeguards are required for responsible AI-driven SME lending?

Research Objectives

The general objective is to examine the opportunities, risks and regulatory responses associated with AI-driven credit assessment and SME access to finance in Africa. Specifically, the study examines its application to SME lending; assesses its effects on financial access and processing efficiency; evaluates alternative-data, bias, privacy and cybersecurity risks; assesses existing regulatory responses; and develops a conceptual framework for responsible AI-driven SME credit assessment.

Significance of the Study

The study provides central banks and financial regulators with evidence for model-governance, fair-lending and supervisory standards. It assists data-protection and cybersecurity authorities in addressing consent, profiling, automated decisions and information security. Banks, microfinance institutions, development finance institutions and fintech providers can use its findings to improve data selection, validation, explainability and borrower-redress procedures. It also helps SMEs and business associations understand the benefits and potential harms of data-driven lending. For the AfDB, African Union and other regional bodies, the analysis supports greater regulatory coordination and minimum continental principles for responsible AI finance. Researchers gain a consolidated basis for further African studies. Overall, the study offers an integrated framework connecting AI capabilities, SME financing outcomes, emerging risks and regulatory safeguards.

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LITERATURE REVIEW

Conceptual Review

Small and Medium-Sized Enterprises in Africa

Small and medium-sized enterprises are independently owned businesses whose employment, turnover, assets or capital remain below nationally prescribed thresholds. No uniform African definition exists. Some jurisdictions classify enterprises mainly by employee numbers, while others combine employment with annual turnover, asset value or sector-specific criteria. Exchange-rate movements, differences in industrial structure and the large informal economy further limit the comparability of monetary thresholds. Consequently, this study treats SMEs according to the official definition applicable in each jurisdiction rather than imposing one national standard on the continent.

Despite this definitional diversity, SMEs perform similar economic functions. They create employment, encourage entrepreneurship, supply larger firms, support local production and broaden the sectoral base of African economies. Their small scale also allows them to operate in rural and underserved markets. The AfDB (2021) nevertheless observes that financing gaps are particularly severe among African micro, small and medium-sized enterprises.

African SMEs span formally incorporated firms with bank accounts, tax records and financial statements, and informal enterprises with limited registration and weak separation between business and household finances. Their funding requirements change across the business cycle. Start-ups require seed capital and working capital; growing firms need inventory, equipment and market-expansion finance; mature firms require longer-term investment, trade and technology finance. Yet informality, weak records, limited managerial capacity, inadequate digital infrastructure, uncertain property rights and shallow credit-information systems restrict formal borrowing. These constraints are mutually reinforcing: firms remain informal partly because finance is scarce, while lenders deny finance because informality reduces verifiable information.

SME Access to Finance

SME access to finance refers to the ability of an enterprise to obtain suitable financial services on reasonable and sustainable terms. It is broader than the existence of a bank account or receipt of a single loan. It encompasses credit availability, probability of approval, interest and related charges, approved amount, processing time, collateral requirements, repayment period, renewal prospects and the inclusion of businesses previously excluded from formal lending.

Access must be distinguished from use. An SME may have access but choose not to borrow because internal funds are adequate or prevailing terms are unattractive. Conversely, actual borrowing may reflect necessity rather than satisfactory access, particularly where a firm accepts a small, expensive, short-term digital loan because no suitable alternative exists. Measures based only on loan uptake can therefore overstate inclusion. Meaningful access exists when appropriate finance is available, affordable, timely and sufficiently flexible to meet the firm’s productive needs.

Digital finance has widened possible entry points into formal credit. However, product suitability remains important. Sanga and Aziakpono (2023) find that fintech can ease SME financing constraints, although its effects depend on the type of technology, institutional environment and characteristics of the enterprise. Thus, higher approval rates should be assessed alongside pricing, loan size, maturity, transparency and repeated access.

Conventional Credit Assessment

Conventional SME credit assessment evaluates repayment capacity through financial statements, credit-bureau records, collateral, bank-account activity, business history and the character and competence of the owner. Loan officers manually verify documents, inspect business premises, assess cash flows and apply internally defined credit rules. Relationship banking supplements formal information with knowledge accumulated through repeated interactions between the borrower and the bank.

These methods can control risk where records are reliable, but they are costly for small loans. Audited accounts and formal credit histories are frequently unavailable among young and informal enterprises, while land titles and other acceptable collateral may be absent or legally uncertain. Rural firms face additional costs because lenders must travel farther to verify operations and monitor loans. Relationship lending also favours established customers over new applicants.

Conventional assessment may consequently interpret missing information as high risk. A profitable enterprise with regular mobile-money receipts but no audited statements can be rejected despite having observable repayment capacity. This approach places young, rural, informal and “thin-file” SMEs at a systematic disadvantage. The World Bank (2022) argues that fintech-based SME finance can address some of these limitations by using digital data and automated processes, although responsible access requires appropriate market-conduct and data safeguards.

Artificial Intelligence-Driven Credit Assessment

AI-driven credit assessment is the use of computational systems that learn from data or apply advanced analytical rules to estimate borrower creditworthiness, default probability, fraud risk or suitable loan terms. Machine-learning models identify nonlinear relationships that conventional scorecards may miss. Predictive analytics estimates future repayment behaviour, while natural-language processing and automated document analysis extract information from invoices, statements, contracts and application forms.

Common models include decision trees, random forests, gradient-boosting methods and neural networks. Decision trees generate rule-based classifications; random forests combine several trees to improve stability; and neural networks detect complex relationships in large datasets. AI-supported fraud systems compare applications with known patterns of identity manipulation or unusual transactions. These tools can feed into automated credit scoring, document verification, loan pricing and portfolio monitoring. A review by Dastile et al. (2020) finds that machine-learning methods have become increasingly prominent in credit scoring because of their capacity to process complex data and improve classification.

AI-assisted and fully automated decisions require distinction. Under AI-assisted assessment, the system produces a score, recommendation or risk alert, but an authorised officer retains responsibility for approval and can consider contextual information. Fully automated assessment generates a binding decision without meaningful human involvement. The latter may reduce processing time further, but it creates greater explainability, accountability and redress concerns because affected borrowers may be unable to identify or challenge the basis of rejection.

Alternative Credit Data

Alternative credit data comprise information not traditionally contained in financial statements or credit-bureau files. They include mobile-money transactions, bank-account cash flows, digital payments, utility and telecommunications payments, e-commerce sales, tax and business-registration records, inventory movements and digital invoices. Some lenders also use social-media activity, online behaviour, geolocation, device characteristics and contact information.

These data can reveal cash-flow regularity, sales trends, payment discipline and business continuity. Mobile-wallet and bank-transaction records have a relatively direct relationship with financial capacity, while tax, inventory and e-commerce records may verify the scale of operations. Digital footprints can complement conventional bureau information and have demonstrated meaningful predictive value (Berg et al., 2020). Alternative data are therefore especially valuable where SMEs lack collateral or established credit files.

Their use is not automatically legitimate. Relevance requires a defensible relationship between the data and repayment risk. Reliability concerns accuracy, completeness and resistance to manipulation. Proportionality asks whether the expected predictive benefit justifies the intrusion. Legality requires a valid basis for collection, clear disclosure, limited retention and protection of data-subject rights. Cash-flow data may satisfy these tests more readily than social-media contacts, device settings or unrelated behavioural indicators. More data can increase prediction while simultaneously weakening privacy and fairness.

Opportunities Associated with AI Credit Assessment

AI can reduce information asymmetry by converting fragmented digital records into indicators of business performance and repayment capacity. This creates a route into formal credit for thin-file SMEs that would otherwise fail documentation or collateral tests. Machine learning may improve default prediction by detecting interactions among cash flow, payment regularity, business seasonality and sector conditions.

Automation also reduces manual verification and underwriting time. Faster processing lowers the cost of assessing small loans, improves scalability and permits providers to serve geographically dispersed firms. Better risk differentiation can support more accurate loan pricing, although improved predictions do not necessarily produce lower prices where markets are uncompetitive. Continuous analysis of transactions can provide early warning of financial distress, strengthen portfolio monitoring and support timely restructuring.

AI-supported identity checks and anomaly detection can reduce application fraud. Providers may also customise credit limits, repayment schedules and working-capital products around observed business cycles. Collectively, these functions can widen lending reach, but their value depends on whether cost savings and improved information translate into larger, affordable and suitable loans rather than merely faster high-cost debt.

Risks Associated with AI Credit Assessment

Algorithmic discrimination arises when a model produces systematically adverse outcomes for particular groups. Direct use of gender or ethnicity may be prohibited, yet location, device type, language, purchasing patterns or digital activity can operate as proxies. Fuster et al. (2022) show that improvements in machine-learning prediction can be distributed unevenly across demographic groups. Garcia et al. (2024) likewise conclude that removing protected variables does not necessarily prevent discrimination because correlated features can reproduce similar outcomes.

Poor-quality or unrepresentative training data can misclassify informal, rural or women-owned businesses. Models may also deteriorate when economic conditions or borrower behaviour change, creating model drift. Complex systems often lack usable explanations, preventing applicants from understanding adverse decisions and making internal validation difficult. Černevičienė and Kabašinskas (2024) find that explainable-AI techniques can improve interpretability in finance, although explanation methods involve trade-offs between simplicity, fidelity and predictive performance.

Excessive collection creates privacy and consent risks, particularly where borrowers must permit broad access to phones or contacts to obtain urgent finance. Data breaches expose financial records and identities, while manipulated inputs can facilitate fraud. Digitally invisible firms may become more disadvantaged as lenders increasingly treat the absence of data as evidence of risk. Easy and rapid credit may also encourage repeat borrowing, predatory pricing and over-indebtedness. These harms become harder to correct where complaint systems are weak, automated decisions cannot be appealed and responsibility is divided among the lender, data provider and model vendor.

Regulatory Safeguards

Responsible AI credit assessment requires layered safeguards rather than reliance on model accuracy alone. Data-protection rules should establish lawful processing, informed consent, purpose limitation, data minimisation, security and restrictions on solely automated decisions. Fair-lending standards should prohibit

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direct and proxy discrimination and require outcome testing across relevant borrower groups. Applicants should receive understandable reasons for adverse decisions and access to human review, correction and appeal.

Financial institutions should document data provenance, feature selection, model purpose, validation results, limitations and approval authority. Independent audits should test accuracy, bias, robustness and compliance before deployment and periodically thereafter. Cybersecurity standards should cover encryption, identity controls, secure software development, penetration testing, breach response and third-party access. Material incidents and model failures should be reported to relevant authorities.

Regulatory sandboxes can support controlled testing, but participation should not exempt providers from consumer, privacy or prudential obligations. Supervisors should also scrutinise cloud providers, scoring vendors and data intermediaries because outsourcing does not remove the lender's responsibility. Complaint and redress arrangements must be accessible to SMEs with limited legal or digital literacy. Aggarwal (2021) maintains that algorithmic credit regulation must balance efficiency, distributive fairness and privacy, while Lainez (2023) emphasises transparency, accessibility and data protection. These safeguards convert responsible AI from a broad ethical aspiration into verifiable institutional practice.

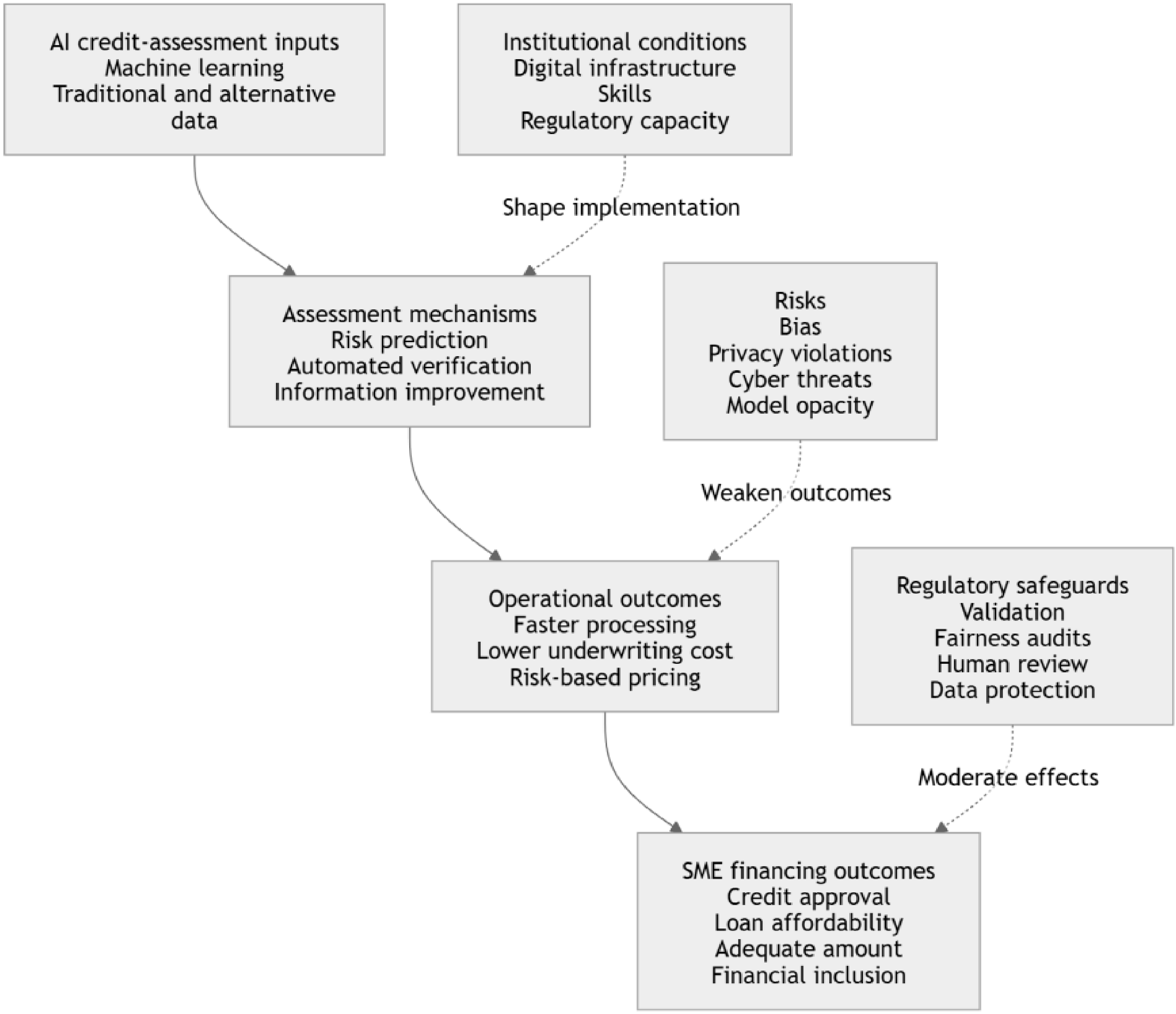

Figure 1: Integrated AI Credit Assessment–SME Financing Framework

Source: Authors' conceptualisation based on the reviewed literature.

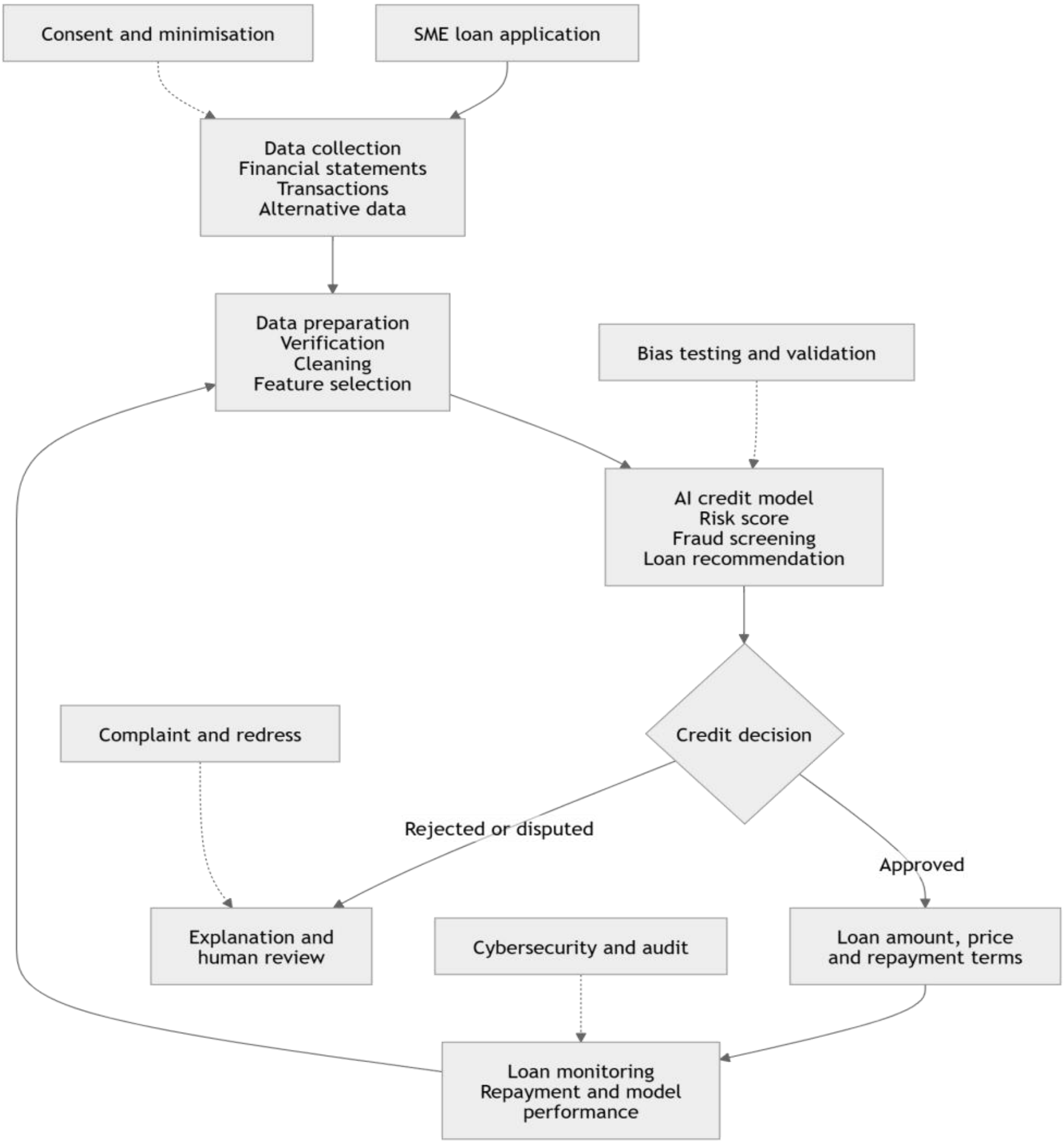

Figure 2: AI-Driven SME Credit Assessment Process and Embedded Safeguards

Source: Authors’ design based on Aggarwal (2021), World Bank (2025) and the reviewed evidence.

THEORETICAL REVIEW

Information Asymmetry Theory principally explains SME credit rationing. Lenders cannot fully observe an enterprise’s repayment capacity, risk profile or intended use of borrowed funds. Before lending, this imbalance creates adverse selection because lenders struggle to distinguish viable SMEs from high-risk applicants. After disbursement, moral hazard may arise when borrowers redirect funds, undertake riskier activities or reduce repayment effort. Financial institutions respond by demanding collateral, audited accounts and credit histories, charging higher interest rates, reducing loan amounts or rejecting applications. Consequently, viable SMEs may remain unfunded because they lack verifiable information rather than productive opportunities (World Bank, 2022; Sanga & Aziakpono, 2023).

AI and alternative data can reduce this imbalance by analysing cash flows, digital payments, sales records and repayment behaviour. Such information can improve borrower screening, lower monitoring costs and support the assessment of thin-file enterprises (Berg et al., 2020). However, inaccurate, outdated or unrepresentative data may create new information problems. Lenders may rely on opaque model outputs that SMEs cannot inspect, understand or correct. Machine-learning improvements may also benefit borrower groups unevenly, especially

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when training data reflect historical inequalities (Fuster et al., 2022). Information Asymmetry Theory therefore explains both AI's inclusion potential and the risk that informational power becomes concentrated in lenders and technology providers.

The Technology–Organisation–Environment framework complements this explanation by identifying the conditions governing AI adoption. The technological dimension covers data quality, system compatibility, predictive accuracy, explainability and cybersecurity. The organisational dimension includes technical expertise, financial resources, management support, model-risk governance and institutional risk culture. The environmental dimension comprises regulation, digital infrastructure, competitive pressure, credit bureaus, data-protection regimes and customer readiness. Fintech's contribution to SME finance therefore depends on the technology itself and the institutional environment in which it operates (Sanga & Aziakpono, 2023).

The theories are complementary. Information Asymmetry Theory explains why viable SMEs experience credit constraints and how richer data may improve lending decisions. The TOE framework explains whether lenders possess the technological, organisational and regulatory conditions required to deploy AI responsibly. Together, they indicate that AI improves SME finance when relevant data are processed by institutions capable of model validation, cybersecurity, accountability and regulatory compliance.

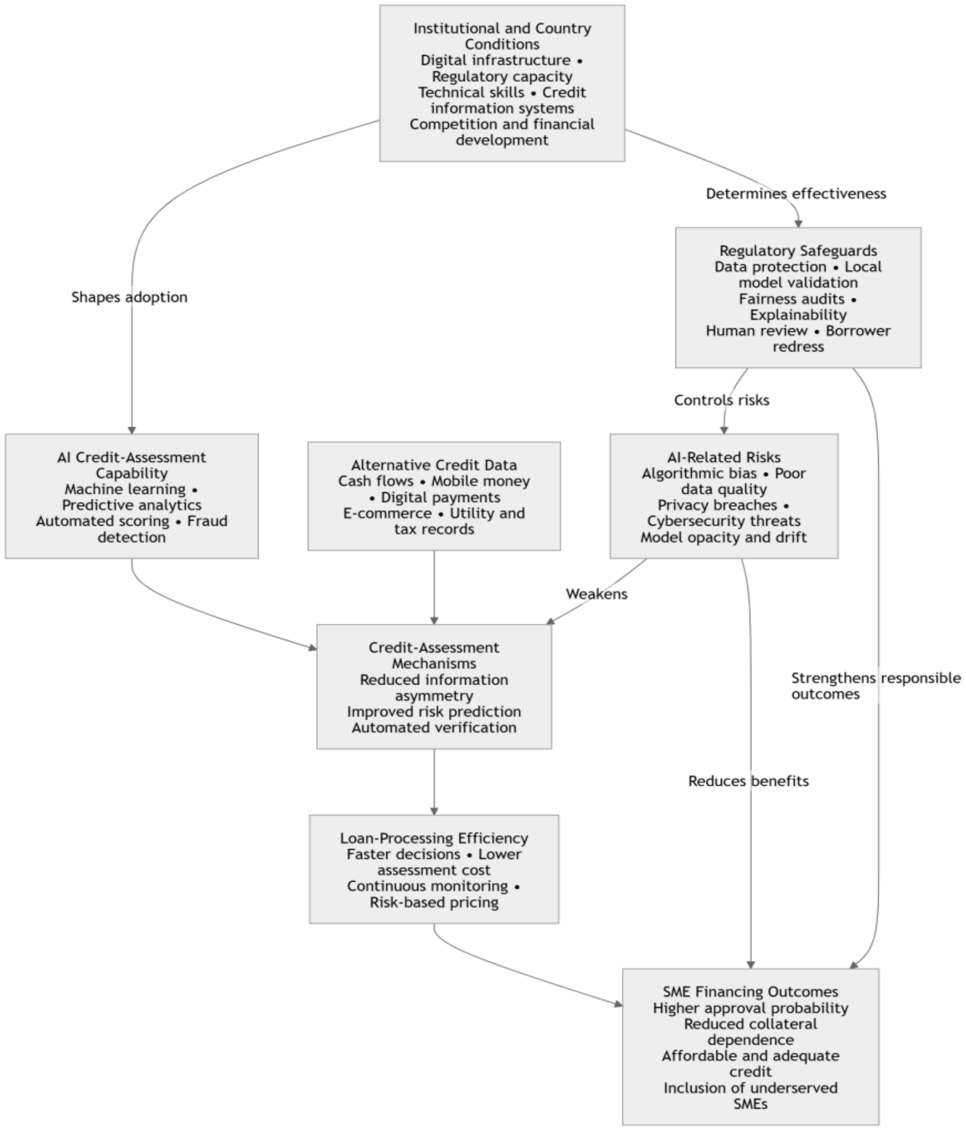

Figure 3: Conceptual Framework for AI-Driven Credit Assessment and SME Access to Finance in Africa

Source: Authors' conceptualisation based on Berg et al. (2020), Aggarwal (2021), Fuster et al. (2022), Sanga and Aziakpono (2023), Omotubora (2024), Mota Makore (2024) and World Bank (2025).

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Empirical Review

Recent evidence generally supports the capacity of AI and fintech to widen SME finance, but it also shows that outcomes depend on data quality, market structure and governance. Using data from informal African merchants, Kazimoto et al. (2025) developed supervised machine-learning models for enterprises lacking conventional financial records and found that tailored scoring could support working-capital assessment. The study is directly relevant to Africa's informal retail sector, though technical prediction does not by itself establish that lenders offer affordable credit or that excluded merchants benefit equally.

A broader review by Abu et al. (2025) concludes that fintech and government support can jointly improve SME financing by reducing information barriers and supporting alternative funding channels. However, the evidence remains uneven across countries and firm types. Studies of fintech platforms also tend to measure finance availability or adoption more readily than interest cost, loan adequacy, collateral reduction and continuity of access. This weakens claims that digital lending always produces substantive inclusion.

Evidence on alternative data is more established. The World Bank (2025) reports that transaction, telecommunications and platform data can expand the assessable population where traditional credit files are incomplete, including through mobile-wallet-based scoring arrangements in Nigeria. Yet the report stresses data quality, consumer consent and governance. Digital records provide useful indicators when they capture business cash flows, but behavioural and device data may create privacy costs disproportionate to their predictive contribution.

In Nigeria, Omotubora (2024) finds that AI-supported alternative data may help women lacking formal credit histories, identification or collateral. The analysis also shows that unequal digital access and gendered privacy concerns can reproduce exclusion. Thus, adding alternative data does not correct historical bias where women generate fewer digital traces or are less willing to surrender sensitive information.

Research on efficiency indicates that automated scoring reduces turnaround time, manual assessment and the marginal cost of processing small loans. Sanga and Aziakpono (2023), reviewing the SME-fintech literature, identify faster processing, improved information and reduced transaction costs as recurring benefits. The World Bank (2022) similarly finds that digital channels support automated underwriting, wider distribution and scalable monitoring. However, provider-level efficiency is not necessarily passed to borrowers through lower prices, especially where a small number of platforms control data, payments and distribution.

The fairness literature remains cautionary. Fuster et al. (2022), using United States mortgage data, find that machine learning improves prediction but can increase disparities because disadvantaged groups do not benefit equally. Bartlett et al. (2022) report that fintech can reduce face-to-face discrimination yet does not eliminate unequal pricing. Although these studies are not African, their mechanisms apply where location, income, gender, informality and digital intensity correlate with historical disadvantage. African models trained on narrow urban or formal-sector datasets may perform poorly for rural and informal enterprises.

Regulatory studies also reveal gaps between innovation and protection. Makore (2024) finds that AI can support financial inclusion in South Africa but argues for a clearer governance framework addressing accountability and cybersecurity. Nigeria's Data Protection Act defines automated decision-making and provides a basis for human intervention and data-subject protection (Nigeria Data Protection Commission, 2023). Nonetheless, translating these general rights into credit-model testing, explanations and timely borrower redress remains an operational challenge.

Kenya provides a more direct digital-credit example. The Central Bank of Kenya's Digital Credit Providers Regulations 2022 introduced licensing and conduct requirements in response to high costs, misuse of personal information and unethical debt collection (Central Bank of Kenya, 2022). However, Upadhyaya (2025) finds that the framework's initial focus on previously unregulated providers left important bank–telecommunications partnerships outside its effective reach. The case demonstrates that entity-based licensing can miss algorithmic and data risks embedded across institutional partnerships.

Across Africa, data-protection laws, digital-lender rules, consumer-credit provisions, cybersecurity requirements and regulatory sandboxes have developed at different speeds. Their fragmentation can leave uncertainty over which authority supervises model fairness, alternative-data legality or third-party scoring vendors. The evidence therefore supports a conditional conclusion: AI can improve risk prediction, processing efficiency and the inclusion of thin-file SMEs, but these gains are neither automatic nor evenly distributed. Effective outcomes require relevant data, locally validated models, competitive lending markets and enforceable safeguards for privacy, security, explanation, human review and redress.

METHODS

Research Design

The study adopted an integrative systematic literature review to examine AI-driven credit assessment, SME financing outcomes, associated risks and regulatory responses in Africa. The design combined the transparency of a systematic review with the breadth of an integrative review. Its systematic component established reproducible procedures for identifying, screening, appraising and selecting publications, while its integrative component permitted the synthesis of evidence derived from different research traditions.

The review covered peer-reviewed quantitative and qualitative studies, conceptual and theoretical articles, credible working papers, legal and regulatory documents, policy reports and institutional publications. This breadth was necessary because AI credit assessment is simultaneously a financial, technological, legal and public-policy issue. Restricting the review to empirical journal articles would have omitted relevant data-protection laws, central-bank regulations, supervisory guidance and policy evidence. The design was therefore suitable for consolidating fragmented evidence while preserving distinctions among empirical findings, legal provisions and policy recommendations. The reporting process followed the transparency principles of the PRISMA 2020 statement (Page et al., 2021).

Review Scope and Population

The review population comprised publications on AI, alternative credit data, automated lending, SME finance and related regulatory issues issued between January 2021 and July 2026. A preliminary search also considered relevant publications from 2020 to identify recent foundational studies and refine the terminology used in the database searches. The final synthesis prioritised evidence published from 2021 onwards, while seminal theoretical works were retained where necessary to explain the intellectual foundations of Information Asymmetry Theory and the Technology–Organisation–Environment framework.

Geographically, the review covered continent-wide African studies, regional evidence, publications from individual African countries and documents issued by African institutions. Relevant evidence from other developing economies was included where similar conditions existed, such as widespread informality, thin credit files, limited collateral and expanding mobile-finance markets. Global studies were admitted when they examined transferable mechanisms, including the predictive value of alternative data, algorithmic discrimination, explainability or model governance. Findings from non-African settings were interpreted cautiously rather than treated as direct evidence of African outcomes.

The unit of analysis was the individual publication. The review population therefore included journal articles, conference papers with sufficient methodological information, working papers, statutes, regulations, supervisory guidelines and institutional reports rather than individual SMEs, lenders or borrowers.

Information Sources

Bibliographic searches covered Scopus, Web of Science, Google Scholar and the Social Science Research Network. Scopus and Web of Science served as the main sources of peer-reviewed multidisciplinary research because their indexing and citation information supported publication verification. SSRN supplied recent working papers in finance, economics, law and technology. SSRN publications were separately identified because repository inclusion does not constitute peer review.

Google Scholar was used for supplementary searching, forward-and-backward citation tracking and locating publications not indexed in the main databases. Its results were subjected to additional verification because coverage is broad and includes materials of uneven quality.

Academic searches were supplemented with publications from the World Bank, International Monetary Fund, African Development Bank and African Union. Regulatory materials were obtained from African central banks, financial-sector regulators, data-protection authorities, cybersecurity agencies and consumer-protection bodies. These institutional sources provided evidence on digital-credit licensing, automated decision-making, data processing, cybersecurity, fair treatment and supervisory sandboxes. Official versions of laws, regulations and guidance were preferred to secondary commentaries.

Search Strategy

The search combined four concept groups: AI technology, SMEs, financing outcomes and geography. The principal search expression was:

("artificial intelligence" OR "machine learning" OR "algorithmic credit scoring" OR "automated credit assessment" OR "automated underwriting") AND ("SME" OR "small business" OR "small and medium enterprise" OR "MSME") AND ("access to finance" OR "credit access" OR "SME finance" OR "digital lending") AND ("Africa" OR "Sub-Saharan Africa" OR the name of an African country)

The search was expanded by combining the principal terms with "alternative data," "mobile money," "financial inclusion," "algorithmic bias," "discrimination," "data protection," "privacy," "cybersecurity," "consumer protection," "explainable AI," "model governance," "financial regulation" and "regulatory sandbox." Country-specific searches were conducted because some publications referred only to a particular jurisdiction without using "Africa" in the title, abstract or keywords.

Search syntax was adapted to the indexing rules of each database. Titles, abstracts and keywords were searched where the database permitted field restrictions. Broader full-text searches were applied to legal and institutional repositories. Reference lists of included publications were examined to locate additional studies, while forward citation tracking identified newer research connected to influential studies. The full database-specific search strings, search dates and filters were documented in an appendix to support reproducibility.

Eligibility Criteria

Publications were included when they satisfied the following criteria:

1. publication between January 2021 and July 2026, apart from selected 2020 foundational evidence;
2. substantive treatment of AI, machine learning, automated credit assessment or alternative credit data;
3. examination of SME finance, digital credit or financial inclusion relevant to enterprise lending;
4. analysis of financing opportunities, technological risks or regulatory responses;
5. African focus or clear transferability to comparable developing-economy conditions;
6. publication as a peer-reviewed article, credible working paper, official legal document or institutional report;
7. availability in English and access to the complete text; and
8. sufficient methodological, analytical, legal or policy information to support evaluation.

The review excluded duplicate records, unverified blogs, commercial promotions and publications unrelated to credit assessment. Studies dealing exclusively with consumer lending were excluded unless their findings on alternative data, algorithmic bias, privacy or regulation had a clear application to SME credit. Publications without accessible full texts, identifiable authorship, verifiable publication details or adequate analytical content were also removed. Opinion pieces were excluded where they offered assertions without empirical, legal or policy support.

Screening and Selection

The database and supplementary searches identified 217 records, comprising 183 records from Scopus, Web of Science, Google Scholar and SSRN and 34 records from institutional repositories, regulatory authorities and citation searching. After removing 71 duplicates, 146 records were screened by title and abstract, of which 83 were excluded for failing to meet the preliminary relevance criteria. Sixty-three publications were sought for full-text assessment, but four could not be retrieved. The remaining 59 publications were assessed against the eligibility and quality criteria. Thirty-nine were excluded because of insufficient African or transferable relevance, exclusive focus on consumer lending, absence of an AI or alternative-data component, inadequate analytical detail, unverifiable publication status or duplication of another publication. The final synthesis comprised 20 publications: 14 peer-reviewed journal articles, four institutional or policy reports and two legal or regulatory documents. The identification, screening, eligibility assessment and final selection of publications are summarised in Figure 2.

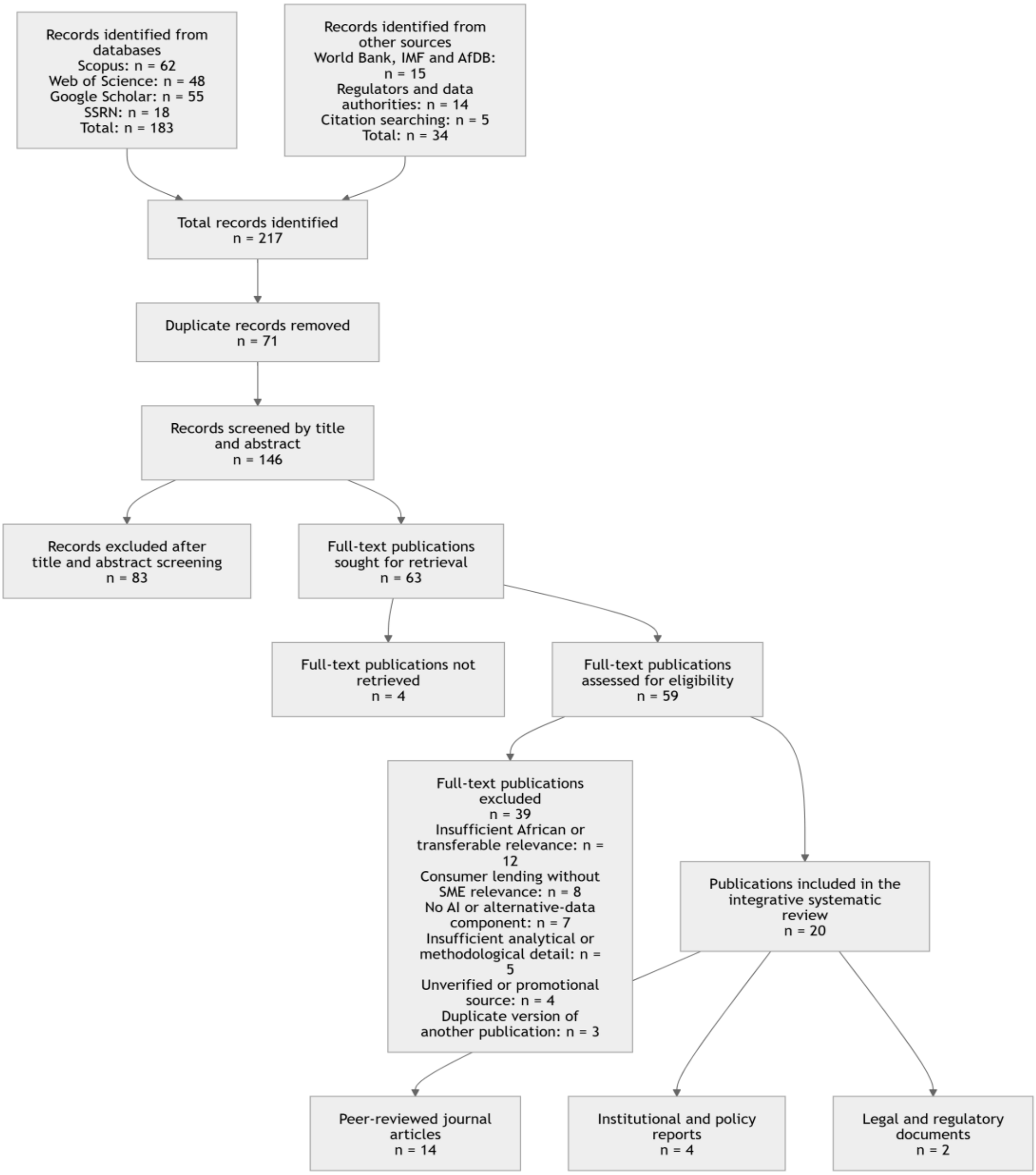

Figure 4: PRISMA Flow Diagram for the Identification, Screening and Selection of Publications

Source: Authors' compilation, adapted from Page et al. (2021).

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Sampling and Sampling Technique

The study used criterion-based purposive sampling. Each publication was selected because it satisfied predetermined requirements relating to period, subject relevance, geographical applicability, source credibility and analytical quality. Random sampling was inappropriate because the purpose was to locate the most relevant body of evidence rather than estimate population characteristics from a probabilistic sample.

Purposive selection also supported the inclusion of authoritative regulatory documents that might not appear in academic databases. To reduce selection bias, the same eligibility criteria were applied across databases and publication types. Citation tracking and searches of official institutional repositories further reduced the risk of omitting relevant evidence.

Quality Appraisal

Included publications were assessed using a structured appraisal matrix. Empirical studies were evaluated according to the relevance of their research questions, clarity of design, appropriateness of data and methods, reliability of findings and transparency about limitations. Conceptual studies were assessed for analytical coherence, engagement with relevant literature and contribution to the review questions. Regulatory and institutional documents were evaluated according to issuing authority, legal status, evidential basis, geographical relevance, and currency.

Each publication was classified as high-, moderate-, or limited-quality evidence. High-quality studies displayed clear methods, credible data, and findings directly relevant to the study. Moderate-quality sources contained useful evidence but had identifiable limitations in design, transferability, or reporting. Limited-quality publications were used only for contextual or emerging issues and were not allowed to determine major conclusions independently. Peer-reviewed status was recorded separately from methodological quality. In particular, working papers obtained through SSRN were not described as peer-reviewed unless publication in a peer-reviewed outlet was verified.

Data Extraction

A standardised extraction form was used to ensure consistency across the selected publications. The form captured:

- author and publication year;
- publication and source type;
- country or region;
- research objective;
- AI or automated-credit application;
- data source and research method;
- type of traditional or alternative credit data;
- SME financing outcome;
- identified opportunities and risks;
- applicable regulatory response;
- principal findings;

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- stated limitations; and
- quality classification.

For legal and regulatory materials, the form additionally recorded the responsible authority, legal status, regulated entities, borrower rights, supervisory obligations and enforcement provisions. This structure allowed empirical findings to be compared with the safeguards available in the relevant jurisdictions.

Method of Analysis

The extracted evidence was analysed through thematic analysis. The process involved familiarisation with the selected publications, initial coding, grouping related codes, developing provisional categories, refining themes, and comparing findings across studies and jurisdictions. The analysis followed the principles of coherence, transparency, and active researcher interpretation identified by Braun and Clarke (2021).

Seven themes guided the synthesis: financial inclusion and SME credit access; alternative credit data; loan-processing efficiency; algorithmic bias and discrimination; privacy and data protection; cybersecurity; and consumer protection and regulatory response. Coding remained sufficiently flexible to accommodate issues emerging from the evidence.

The analysis compared areas of agreement, contradiction, and evidential weakness rather than merely summarising publications individually. Particular attention was given to differences between technical performance and substantive financing outcomes. For example, higher predictive accuracy was not treated as improved financial inclusion unless the evidence also indicated favourable effects on approval, pricing, collateral, loan size or borrower coverage. African findings were compared across institutional and regulatory contexts, while non-African evidence was assessed for transferability.

Evidence-Synthesis Model

Because the study synthesised existing evidence rather than analysing primary numerical data, it did not estimate an econometric model. The conceptual relationship guiding the synthesis was specified as:

$$\mathbf{SFO=f(AIC,ACD,LPE,RSK,RGS,IC)}$$

where SFOSFOSFO represents SME financing outcomes; AICAICAIC denotes AI credit-assessment capability; ACDACDACD represents the availability and quality of alternative credit data; LPELPELPE denotes loan-processing efficiency; RSKRSKRSK comprises algorithmic, privacy and cybersecurity risks; RGSRGSRGS represents regulatory safeguards; and ICICIC captures institutional and country conditions.

The expected relationships were expressed conceptually as:

$$\mathbf{SFO=\beta_0+\beta_1 AIC+\beta_2 ACD+\beta_3 LPE-\beta_4 RSK+\beta_5 RGS+\beta_6 (AIC\times RGS)+\varepsilon}$$

The formulation indicates that AI capability, reliable alternative data and processing efficiency are expected to improve SME financing outcomes, whereas uncontrolled risks may weaken them. Regulatory safeguards exert a direct positive influence and moderate the effect of AI capability by making its deployment more transparent, secure and accountable. Institutional conditions determine whether these relationships operate effectively across African jurisdictions. The equation served only as an evidence-synthesis framework; its coefficients were neither statistically estimated nor presented as empirical results.

For subsequent empirical validation, the framework can be operationalised through measurable constructs. AI credit-assessment capability may be measured by the number of automated underwriting functions, degree of decision automation, model-update frequency and staff AI competence. Alternative-data quality may be captured through completeness, accuracy, timeliness, representativeness and lawful provenance. Loan-processing efficiency can be measured by turnaround time, cost per application and manual-review share. SME financing outcomes may include approval probability, annual percentage cost, collateral requirement, loan size, maturity, repeat access and default. Risk constructs may be measured through subgroup false-negative gaps, complaint incidence, data breaches, model drift and explanation failure. Regulatory safeguards may be represented by independent validation, impact assessment, audit frequency, human-review rights and enforcement activity, while country conditions may include digital-payment use, identification coverage, credit-bureau coverage, connectivity and supervisory technical capacity. Survey items can use multi-item five-point scales, complemented by lender records and regulatory data; reliability, measurement invariance and structural relationships can then be tested through confirmatory factor analysis and multilevel or structural-equation models.

FINDINGS AND DISCUSSION

Characteristics of Included Studies

The final evidence base comprised 20 publications, including 14 peer-reviewed journal articles, four institutional or policy reports and two legal or regulatory documents. The publications covered the period from 2020 to 2025, with the 2020 studies retained as recent foundational evidence and the remaining sources concentrated between 2021 and 2025. The geographical evidence covered Africa generally and selected jurisdictions, particularly Nigeria, Kenya and South Africa, while relevant global and developing-economy studies were included where their findings were transferable to African SME credit markets.

The studies examined commercial banks, microfinance institutions, fintech lenders, digital-credit providers, mobile-network operators, and development finance institutions. Quantitative studies used loan files, transaction histories, credit-bureau data, mobile-money records and digital footprints. Qualitative and legal studies examined borrower experiences, lending practices, privacy, automated decision-making and regulatory frameworks. The principal AI methods included decision trees, random forests, gradient boosting, neural networks, predictive analytic and natural-language processing.

The exact numerical distribution should be inserted from the completed PRISMA screening log. Reporting estimated figures would weaken the reprehensibility of the study.

Table 1: Profile of the review evidence

Characteristic	Main pattern identified
Publication period	Evidence increased substantially after 2022
Geographical coverage	Nigeria, Kenya, South Africa, Ghana and Rwanda dominated country-level evidence
Publication types	Empirical articles, systematic reviews, legal studies, working papers and official reports
Research designs	Quantitative modelling, qualitative analysis, case studies, legal analysis and evidence synthesis
Lending institutions	Banks, microfinance institutions, fintech lenders, mobile-network partnerships and development institutions
AI methods	Decision trees, random forests, neural networks, gradient boosting and predictive analytics
Data sources	Bank transactions, mobile money, digital payments, e-commerce, utility records and credit-bureau data
Main evidential limitation	Limited African loan-level evidence linking AI scores to long-term SME financing outcomes

AI Credit Assessment and Financial Inclusion

The evidence indicates that AI can expand the assessable population of SMEs, particularly where conventional underwriting excludes firms without collateral, audited accounts or formal credit histories. Machine-learning

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models process cash-flow and transaction information that may reveal business viability even when standard credit files are incomplete. Digital footprints can complement credit-bureau information and provide useful repayment signals (Berg et al., 2020). Sanga and Aziakpono (2023) similarly find that fintech reduces some information and transaction barriers affecting SME finance.

The strongest inclusion potential concerns thin-file and informal enterprises. Evidence from informal African merchants suggests that supervised machine-learning models can estimate working-capital risk using information suited to enterprises outside conventional accounting systems (Kazimoto et al., 2025). AI may therefore shift assessment from asset ownership towards observed business activity. This benefits young firms and SMEs without conventional collateral, provided they generate reliable transaction records.

The evidence for women-owned SMEs is more conditional. Alternative data may compensate for limited collateral and credit histories, but unequal access to phones, identification, bank accounts and digital platforms produces gendered data gaps. Omotubora (2024) finds that AI can support women's financial inclusion in Nigeria while also reproducing exclusion where product design and training data ignore women's circumstances. Privacy concerns may further reduce women's willingness to provide behavioural or personal data.

Rural firms face a similar tension. Remote assessment lowers travel and branch costs and can extend lending beyond urban centres. However, weak connectivity, limited digital-payment acceptance and irregular electronic records can make rural enterprises less visible to data-driven models. AI therefore tends to benefit digitally active thin-file firms more readily than genuinely data-poor enterprises. The findings distinguish data-supported inclusion from universal inclusion: firms without conventional records but with digital trails may gain access, while firms lacking both remain disadvantaged.

Improved approval probability also does not necessarily mean suitable finance. Some digital lenders provide small, short-term and expensive loans that do not match SME investment cycles. Financial inclusion should therefore be judged by affordability, adequacy, maturity, collateral reduction and continuity of access rather than the speed or number of approvals alone.

Alternative Credit Data and Creditworthiness Evaluation

Transaction and cash-flow data emerged as the most defensible alternatives to conventional credit information. Bank deposits, mobile-money receipts, digital payments and e-commerce sales directly indicate revenue patterns, liquidity and business continuity. Utility and telecommunications payments may reveal payment discipline, while tax, registration and invoice records can verify enterprise identity and operating scale. The World Bank (2025) reports that alternative data can extend credit assessment to borrowers lacking conventional files, including through telecommunications and mobile-wallet arrangements.

Predictive usefulness nevertheless varies by data category. Business cash flows have a clearer connection to repayment capacity than social-media activity, contact lists, device settings or browsing behaviour. The latter may add statistical power but provide weak economic explanations for adverse decisions. Their collection may therefore be disproportionate even where technically predictive.

Reliability also remains uneven. Cash-based sales may be missing from digital records, while shared phones and mobile wallets can blur the distinction between personal and business activity. Platform data may cover only one part of an enterprise's operations. Transaction histories can be manipulated through artificial transfers, and temporary sales increases may be mistaken for stable capacity. Models must therefore test data completeness, consistency and resistance to manipulation rather than assume that digitally recorded information is accurate.

Representativeness presents a deeper concern. Training data from successful urban borrowers may not reflect informal, rural or women-owned firms. SMEs rejected under earlier lending rules may be absent from the outcome data, meaning the model learns only from applicants previously accepted. This selection problem can preserve historical exclusion.

Data ownership and consent are similarly unsettled. Banks, telecommunications providers, e-commerce platforms and fintech lenders may each control parts of an SME's digital record. Consent obtained through lengthy application terms may be legal in form but weak in substance when finance depends on accepting extensive phone permissions. Geolocation, language, handset type and transaction location may also operate as proxies for income, gender, ethnicity or rural residence. Alternative data improve credit assessment only where their relevance, reliability, representativeness and lawful use are demonstrated.

Limitations of AI Models in Low-Data Environments

The usefulness of AI is constrained where SME data are sparse, intermittent or generated through channels that exclude cash-based and informally operated firms. A model trained mainly on urban, banked and digitally active enterprises may achieve acceptable aggregate accuracy while producing poorly calibrated probabilities for rural firms, start-ups, women-owned businesses and enterprises affected by network or electricity disruptions. Missing observations are not random in these settings: digital invisibility often reflects structural exclusion. Treating the absence of a digital record as evidence of weak creditworthiness therefore embeds infrastructure inequality in the score.

Small and rapidly changing datasets also limit the stability of complex machine-learning models. High-dimensional behavioural variables can overfit a narrow development sample, while economic shocks, currency instability, platform changes and migration between mobile networks alter relationships learned during training. Models imported from another country face an additional transportability problem because repayment behaviour, identity systems, business informality, consumer law and digital-payment use differ materially. Synthetic data and transfer learning may supplement scarce observations, but they can reproduce assumptions embedded in the source data and cannot substitute for representative local validation.

Practical deployment in low-data markets should therefore favour parsimonious and interpretable models where these perform comparably, combine digital traces with verified business cash-flow information, record uncertainty around individual predictions and refer borderline cases for human assessment. Lenders should publish performance by relevant subgroups and test calibration, false-negative rates and stability over time. Where sample sizes are too small to support a reliable subgroup conclusion, the appropriate response is restricted deployment or further data collection, rather than an unsupported claim of fairness.

Loan-Processing Efficiency and Lending Costs

The literature consistently identifies operational efficiency as a major benefit of AI lending. Automated document extraction, identity verification, fraud screening and credit scoring reduce the time required to evaluate small applications. Decisions that previously required branch visits and manual review can be completed electronically. These savings are important because conventional underwriting costs represent a larger proportion of a small loan than of a corporate facility.

AI also supports scale. Once developed and integrated, a model can assess large application volumes at relatively low marginal cost, update risk estimates and identify changes in portfolio performance. Automated anomaly detection can flag inconsistent identities, duplicated applications and unusual transaction patterns. Sanga and Aziakpono (2023) identify faster processing and reduced information costs as recurring channels through which fintech supports SME lending, while the World Bank (2022) reports that digital platforms can widen distribution and improve underwriting efficiency.

However, lower administrative cost does not automatically reduce the borrower's interest rate. Pricing also reflects funding cost, expected default, market power, loan maturity and the provider's commercial strategy. Where few firms control payments, data and lending platforms, efficiency gains may be retained as profit. Rapid approval may even support expensive short-term lending if providers prioritise volume over suitability.

The effect on portfolio performance is also conditional. Better prediction can reduce defaults and improve risk-based pricing, but model errors may scale quickly when automated across thousands of borrowers. Fraud models

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can generate false positives, while continuous monitoring may produce frequent credit-limit changes that destabilise business planning. Operational efficiency is therefore beneficial when accompanied by model validation, human escalation and evidence that cost savings improve loan terms.

Table 2: Main opportunities and limiting conditions

Opportunity	Expected financing effect	Limiting condition
Alternative-data assessment	Inclusion of thin-file SMEs	Unequal digital records and poor data quality
Automated underwriting	Faster decisions and lower processing cost	Weak explanations and excessive automation
Risk differentiation	More accurate pricing and loan limits	Bias, market power and unstable models
Remote assessment	Wider rural reach	Connectivity and digital-literacy constraints
Continuous monitoring	Earlier detection of distress	Intrusive surveillance and abrupt limit changes
Fraud analytics	Reduced identity and application fraud	False positives and manipulated inputs
Product customisation	Better alignment with cash-flow cycles	Predatory personalisation or over-lending

Algorithmic Bias and Exclusion Risks

The findings show that algorithmic neutrality cannot be assumed. Models learn relationships from historical data, including patterns created by earlier discrimination, geographical inequality and unequal access to formal finance. If past borrowers were mainly urban, male-owned and formally registered enterprises, the model may treat those characteristics or their proxies as indicators of lower risk.

Removing protected characteristics does not resolve the problem because location, device ownership, language and transaction behaviour can reproduce them. Garcia et al. (2024) find that credit models can generate discriminatory outcomes through correlated variables even when protected attributes are excluded. Fuster et al. (2022) similarly show that machine learning improves overall prediction while distributing benefits unevenly among borrower groups.

Digital inactivity creates another exclusion mechanism. Firms operating largely in cash may receive weak scores because the model interprets limited data as limited capacity. Rural and informal businesses may therefore be excluded for data scarcity rather than default risk. This represents a shift from collateral exclusion to digital-data exclusion.

Black-box models aggravate these effects. A lender may know that a score falls below its threshold without being able to provide a meaningful reason. Applicants cannot correct errors or change behaviour when explanations are generic. Explainable-AI methods can improve interpretation, but their usefulness depends on whether explanations accurately reflect the model and can be understood by borrowers and credit officers (Černevičienė & Kabašinskas, 2024).

Model drift is particularly relevant in volatile African economies. Inflation, currency depreciation, policy changes, conflict or climate shocks can alter relationships learned from historical data. Imported models may also fail because repayment behaviour and digital-finance structures differ across countries. Local validation, subgroup testing and continuous performance monitoring are therefore necessary before automated models determine access or pricing.

Privacy and Data-Protection Risks

AI credit assessment expands both the volume and sensitivity of borrower information. Lawful processing requires a recognised legal basis, clear notice and a defined purpose. Consent should specify the data accessed, reason for use, third parties involved and consequences of refusal. Broad consent bundled into an urgent loan application may not represent an informed or freely considered choice.

Purpose limitation requires data collected for payment, communication or platform use not to be automatically repurposed for credit scoring without legal authority and adequate disclosure. Data minimisation further requires providers to use only information necessary for a defensible credit objective. Access to contact lists, messages or unrelated applications is difficult to justify where transaction data provide an adequate assessment.

Automated-decision rights remain important because credit rejection can materially affect an enterprise. Nigeria's Data Protection Act 2023 recognises decisions based solely on automated processing and provides a basis for data-subject protections (Nigeria Data Protection Commission, 2023). Yet practical enforcement requires lenders to identify automated decisions, preserve decision records and provide effective human reconsideration.

Cross-border processing creates further uncertainty where models, cloud services or vendors operate outside the borrower's jurisdiction. Providers must establish lawful transfer mechanisms and ensure that foreign processors meet required security and privacy standards. Retention periods should be linked to the credit relationship and regulatory requirements. Indefinite retention increases breach risk and allows outdated information to influence future applications. SMEs should be able to access, correct and, where legally permissible, request deletion of inaccurate or unnecessary data.

Cybersecurity Risks

Alternative-data lending creates concentrated stores of identity, transaction and behavioural information. A breach can expose both personal and commercially sensitive SME data, while stolen credentials may support fraudulent borrowing. Attackers may manipulate transaction records, digital identities or application inputs to produce favourable scores. These risks affect borrowers and can undermine the integrity of lenders' portfolios.

Dependence on external scoring vendors, cloud infrastructure, telecommunications companies and application-programming interfaces expands the attack surface. A lender may maintain adequate internal controls while remaining exposed through a weak third party. Concentration in a small number of cloud or model providers can also create common vulnerabilities across financial institutions.

Minimum safeguards include encryption, multifactor authentication, access controls, secure software development, independent penetration testing and continuous monitoring. Providers require tested incident-response and business-continuity arrangements, including procedures for correcting affected scores and notifying regulators and borrowers. Incident reporting should cover model compromise and data manipulation, not merely conventional breaches. Operational resilience also requires lenders to continue essential services when automated systems or third-party connections fail.

Consumer and SME Borrower Protection

Responsible digital lending requires clear disclosure of interest, fees, repayment schedules, default charges and total borrowing cost before acceptance. Product terms should be understandable on a mobile device and should not depend on hidden or preselected consent. Borrowers also require specific reasons for rejection or unfavourable pricing rather than generic statements that they failed an internal assessment.

SMEs should be able to access the data used, correct inaccuracies and request human reconsideration of contested automated decisions. A meaningful appeal requires a reviewer with authority to depart from the model, not a second automated assessment. Providers should maintain accessible complaint channels and time-bound dispute resolution.

Easy repeat borrowing creates over-indebtedness risk. Automated systems should consider existing obligations and repayment capacity rather than maximise loan uptake. Debt collection must avoid harassment, unauthorised contact with third parties and public disclosure of default. Kenya's Digital Credit Providers Regulations require confidentiality, clear terms, creditworthiness assessment and complaint mechanisms (Central Bank of Kenya, 2022). These protections are useful, although their effectiveness depends on supervision, coverage and enforceable sanctions.

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Assessment of African Regulatory Responses

Country differences show that AI-credit readiness cannot be inferred from the existence of a data-protection law alone. Adoption depends on the depth of digital payments, identity and credit-information infrastructure; regulatory maturity depends on whether general legal rights have been translated into enforceable credit-model obligations. Kenya, Nigeria, South Africa, Ghana and Rwanda occupy different positions on these dimensions, and none yet provides a complete regime for model fairness, local validation, cybersecurity, third-party accountability and SME redress.

Table 3: Comparative synthesis of AI-credit readiness, regulation and implementation challenges

Source: Authors' synthesis based on Central Bank of Kenya (2022), Nigeria Data Protection Commission (2023), Mota Makore (2024), Bank of Ghana (2025), and Ministry of ICT and Innovation (2023).

Country	AI adoption and digital infrastructure	Principal framework	Regulatory maturity	Main implementation challenge
Kenya	High mobile-money and digital-credit use; strong transaction-data availability	CBK Digital Credit Providers Regulations 2022; data-protection law	Relatively advanced provider licensing and conduct supervision; limited public AI-audit rules	Coverage of bank–telecom partnerships; local fairness testing; supervisory access to vendor models
Nigeria	Large fintech and payments market; uneven identity, credit-file and connectivity coverage	Nigeria Data Protection Act 2023; sectoral financial and consumer rules	Strong general automated-decision rights, but fragmented institutional responsibility	Coordination among regulators; enforcement scale; rural and informal-enterprise data gaps
South Africa	Mature banking and credit-bureau systems; stronger institutional capacity	POPIA, especially section 71; financial-sector and equality law	Developed privacy and financial supervision; limited credit-specific AI standards	Operational explanation standards; subgroup audits; governance of proprietary models
Ghana	Growing mobile-money and digital-credit market; developing open-finance infrastructure	Data Protection Act 2012; Digital Credit Services Providers Directive 2025	Formal digital-credit regime is emerging; automated-decision rights already recognised	Implementation capacity; consistent licensing; monitoring data use and affordability
Rwanda	Coordinated digital-policy architecture; expanding digital identity and payments; smaller market	Personal Data and Privacy Law 2021; National AI Policy 2023	Clear responsible-AI policy direction; fewer credit-specific model rules	Limited representative training data; specialist skills; converting policy into enforceable supervision

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Kenya has the clearest direct digital-credit licensing regime among the selected cases and benefits from extensive mobile-money use, but the rules focus more on provider conduct, information security and data collection than on algorithmic audit standards. Structural concentration in bank–telecommunications partnerships can also limit the reach of rules aimed initially at previously unregulated lenders (Upadhyaya et al., 2025). Nigeria offers a large fintech market and extensive payment activity, while the Nigeria Data Protection Act 2023 provides rights concerning solely automated decisions. Implementation is harder because responsibility is dispersed across financial, competition and consumer-protection, data-protection and cybersecurity authorities. South Africa combines mature banking, credit-bureau and data-protection institutions; section 71 of POPIA regulates significant solely automated decisions, but credit-specific fairness thresholds, explanation formats and AI-model audit rules remain underdeveloped (Mota Makore, 2024). Ghana's Data Protection Act recognises rights related to automated decision-taking, and its Digital Credit Services Providers Directive formalises licensing and conduct oversight, yet supervisory capacity and implementation consistency remain central concerns (Bank of Ghana, 2025). Rwanda's National AI Policy and data-protection law provide a coordinated policy direction for responsible AI, but its smaller credit market, limited local training data and need for specialised supervisory expertise constrain implementation (Ministry of ICT and Innovation, 2023). These contrasts confirm the TOE proposition that infrastructure, organisational capability and regulatory enforcement jointly condition outcomes.

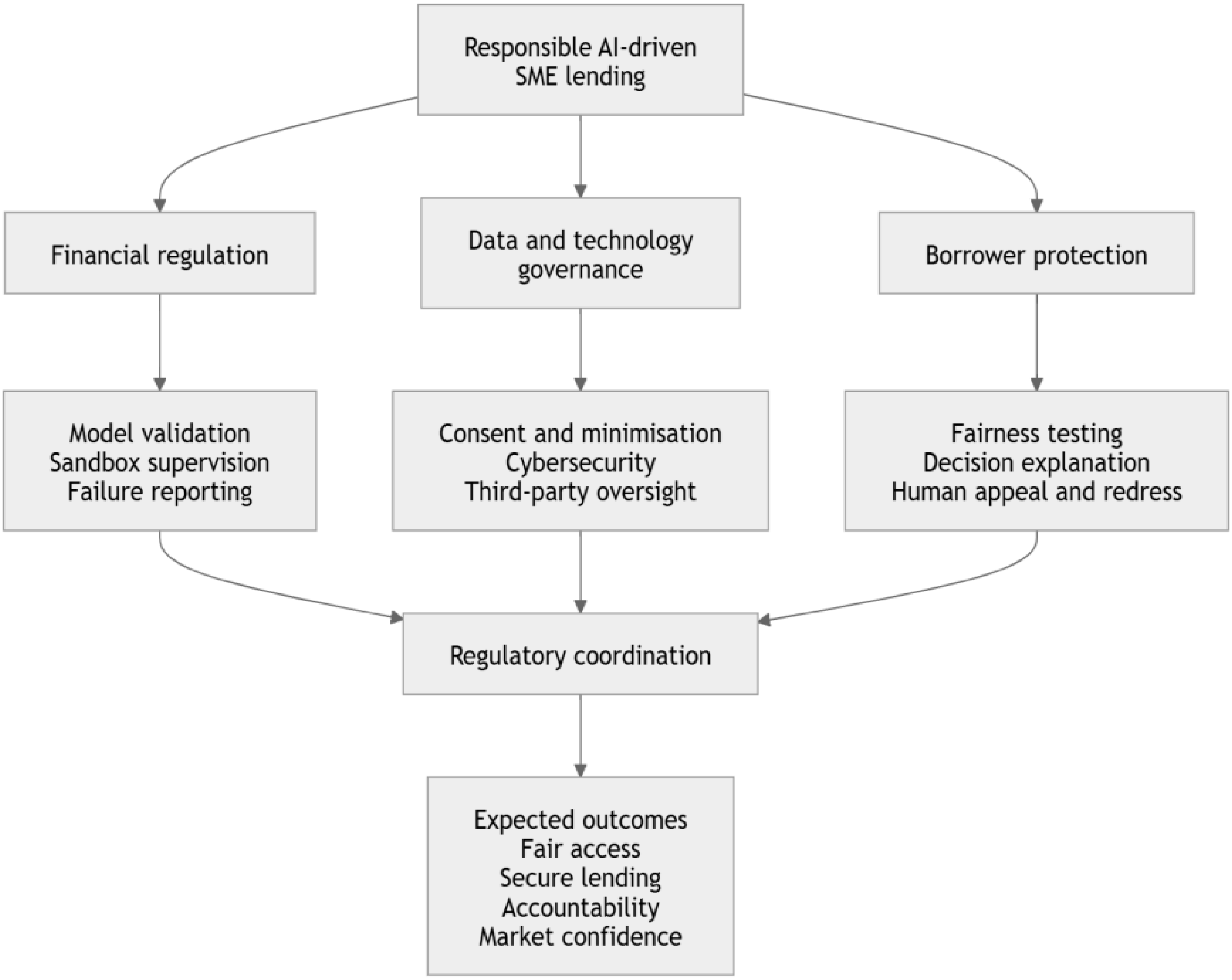

Figure 5: African Responsible AI Credit Regulation Framework

Source: Authors' conceptualisation based on the Central Bank of Kenya (2022), Nigeria Data Protection Commission (2023), Mota Makore (2024) and Upadhyaya et al. (2025).

Integrated Discussion

The evidence supports Information Asymmetry Theory but modifies its conventional interpretation. AI and alternative data reduce lenders' uncertainty by revealing cash flow, payment behaviour and business continuity. This can ease adverse selection and lower screening costs. However, opaque models create a new asymmetry in which lenders and vendors understand the decision process more fully than SMEs. Information inequality is therefore reduced in one direction and intensified in another.

The TOE framework explains why identical technologies produce different outcomes. Technologically, data quality, local validation, explainability and security determine model reliability. Organisationally, outcomes depend on skills, governance, financial capacity and willingness to challenge vendor systems. Environmentally, digital infrastructure, competition, credit bureaus, privacy enforcement and supervisory coordination shape whether efficiency translates into responsible access.

The evidence also resolves an apparent contradiction in previous studies. AI can improve predictive accuracy and still worsen exclusion; automation can reduce processing costs without lowering interest rates; and digital lending can expand loan uptake without providing suitable SME finance. These outcomes are not inconsistent. They reflect differences between technical performance, provider efficiency and borrower welfare.

Overall, AI-driven credit assessment offers its greatest benefit where SMEs possess useful digital business records but lack conventional credit files. Its weakest performance occurs where firms are digitally invisible, models are imported without local testing, markets are concentrated and regulatory rights cannot be enforced. The central finding is therefore conditional: AI can improve SME access to finance in Africa when relevant data, competent institutions, competitive markets and enforceable safeguards operate together. Without these conditions, it may replace collateral-based exclusion with data-driven exclusion.

SUMMARY, RECOMMENDATIONS AND CONCLUSION

Summary of Major Findings

This study examined the opportunities, risks and regulatory responses associated with AI-driven credit assessment and SME access to finance in Africa. The evidence was synthesised according to five objectives.

First, AI-driven credit assessment is applied through machine learning, predictive analytics, automated document analysis, fraud detection and algorithmic underwriting. Banks and fintech providers increasingly combine these technologies with mobile-money records, bank-account cash flows, digital payments, e-commerce sales, utility payments and credit-bureau information. The application remains uneven across Africa and is concentrated in countries with relatively developed digital-finance markets, including Kenya, Nigeria, South Africa, Ghana and Rwanda.

Second, AI can improve SME access to finance by reducing information asymmetry and the cost of evaluating small loans. Alternative data allow lenders to assess thin-file and informal enterprises that lack audited accounts, conventional collateral or established credit histories. Automated verification and scoring also shorten processing time and permit lenders to assess large volumes of applications. Digital footprints can provide useful information beyond traditional credit-bureau records (Berg et al., 2020), while fintech generally supports SME finance through lower information and transaction costs (Sanga & Aziakpono, 2023). These benefits are nevertheless conditional. Faster approval does not necessarily produce affordable interest rates, adequate loan amounts, suitable repayment periods or continuing access.

Third, AI credit assessment creates significant data, fairness and security risks. Models trained on incomplete or unrepresentative data may disadvantage women-owned, rural, informal, young and digitally inactive firms. Removing gender, ethnicity or other protected characteristics does not eliminate discrimination because location, device type and behavioural data can operate as proxies. Machine learning may improve overall prediction while distributing its benefits unevenly among borrower groups (Fuster et al., 2022). Opaque decisions, model drift, cyberattacks, identity theft and excessive personal-data collection can further weaken borrower welfare.

Fourth, African regulatory responses have expanded but remain fragmented. Kenya has introduced direct licensing and market-conduct requirements for digital-credit providers, while Nigeria's Data Protection Act 2023 recognises automated decision-making and related data-subject protections. South Africa, Ghana and Rwanda also provide relevant data-protection or responsible-AI provisions. However, most jurisdictions lack comprehensive credit-specific requirements for algorithmic fairness testing, local model validation, independent auditing and third-party AI oversight. General financial and data-protection rules may apply, but institutional mandates and enforcement responsibilities are not always clear.

Fifth, the study developed an integrated framework in which AI capability, alternative-data quality and loan-processing efficiency influence SME financing outcomes. Algorithmic, privacy and cybersecurity risks can weaken these outcomes, while regulatory safeguards moderate the relationship by improving fairness, security, explainability and accountability. AI therefore contributes to SME finance only when technological capacity is supported by suitable organisational governance and an effective regulatory environment.

Recommendations

Central Banks and Financial Regulators

African central banks and financial regulators should establish proportionate AI credit-model governance standards covering data provenance, model development, approval, validation, monitoring and retirement. High-impact models used to approve, reject, price or limit SME credit should undergo independent validation before deployment and after material modification.

Regulators should require local performance testing rather than accept results obtained from foreign or commercially restricted datasets. Validation should report overall discrimination and calibration together with approval-rate, pricing, false-positive and false-negative differences across gender, location, firm age, formality and other legally relevant groups. Authorities may initially require providers to justify any material disparity, investigate its cause and implement a time-bound remediation plan rather than impose one universal numerical threshold on unlike markets. Results should be filed before deployment, at least annually, after material model changes and whenever drift or complaints indicate possible harm. Material failures, discriminatory outcomes and security incidents should be reported within prescribed periods.

Supervisory agencies should develop staff competence in data science, model risk, cybersecurity and algorithmic auditing. Regulatory sandboxes can support controlled experimentation, but participation should not exempt providers from privacy, consumer-protection or fair-treatment obligations. Sandbox approvals should be time-bound and conditional on clearly defined testing, reporting and exit requirements.

Data-Protection and Cybersecurity Authorities

Data-protection authorities should issue credit-specific guidance on profiling, alternative data and solely automated decisions. Providers should disclose what information is collected, its source, purpose, retention period and effect on the lending decision. Consent should be specific and understandable rather than buried in lengthy application terms.

Authorities should enforce purpose limitation and data minimisation. Contact lists, private communications, social-media activity and device information should not be used where less intrusive financial data provide an adequate assessment. High-risk credit systems should undergo data-protection impact assessments before deployment.

Cross-border transfers of SME data should occur only under recognised legal safeguards. Cybersecurity authorities should coordinate minimum requirements for encryption, access control, breach notification, penetration testing and incident response. Borrowers should be informed where a security breach could affect their identity, financial records or credit score.

Financial Institutions and Fintech Providers

Financial institutions should retain meaningful human review for disputed, unusual and high-impact decisions. The reviewer must have adequate information and authority to alter an automated outcome. Regulators should prescribe a minimum adverse-decision notice containing the decision, the principal data sources, the three to five factors that most influenced the outcome, how the applicant may correct data, and the route and deadline for human reconsideration. An explanation should be faithful to the actual model, understandable without technical expertise and specific enough to support an appeal; disclosure of source code is unnecessary.

Providers should conduct periodic fairness tests across gender, location, firm age, formality and other relevant characteristics. Tests should examine approval and pricing disparities, loan limits, calibration within groups and false-rejection rates, with confidence intervals and minimum sample-size rules. Where protected attributes cannot lawfully be used in production, regulators should permit controlled audit environments with strict access and retention controls. Model performance should be monitored monthly or quarterly according to risk, with formal revalidation at least annually and after major economic, data or model changes.

Banks and fintech firms should use alternative data according to its relevance to creditworthiness. Business cash flows, digital sales and payment histories generally have a clearer financial basis than social-media behaviour or phone contacts. Third-party scoring and cloud-service agreements should assign responsibility for data accuracy, security, model validation, audit access and incident reporting. Outsourcing a model should not transfer accountability away from the lender.

African Regional Institutions

The African Union, AfDB and regional economic communities should translate the Continental AI Strategy into minimum regional principles for high-impact credit systems. A common supervisory template should define model documentation, fairness indicators, explanation content, human-review rights, cybersecurity, cross-border data safeguards, vendor accountability and borrower redress while allowing national authorities to impose stricter requirements (African Union Commission, 2024). Mutual notification arrangements should cover material model failures, cyber incidents and enforcement actions affecting providers operating in several countries.

Regional institutions should support interoperable but privacy-preserving digital identity, credit-reporting and consent-based data-sharing standards. Supervisory colleges can coordinate inspections of fintech lenders, cloud providers and model vendors operating in several countries, using a lead-regulator arrangement without removing each national authority’s enforcement power. Shared algorithmic-audit facilities, standard reporting schemas and a regional register of high-impact credit models would reduce duplication and assist regulators that cannot independently maintain specialised technical teams.

SME Associations and Development Institutions

SME associations, chambers of commerce and development finance institutions should improve borrowers’ digital and financial literacy. Training should cover total borrowing cost, data permissions, digital security, credit-report correction and complaint procedures. SMEs should also be supported to formalise operations, separate business and personal finances and maintain reliable digital sales and cash-flow records. These practices can improve assessment without requiring intrusive behavioural data.

CONCLUSION

AI-driven credit assessment can reduce information gaps, lower underwriting costs and extend finance to African SMEs excluded by collateral requirements and limited credit histories. The opportunity is greatest in digitally connected markets with reliable transaction data and capable supervisors, and weakest where sparse records, infrastructure gaps and imported models undermine calibration and fairness. Country comparison confirms that general privacy rights and national AI policies must be converted into enforceable credit-model duties. Predictive accuracy alone is an inadequate measure of success. Responsible adoption requires locally validated performance, measurable subgroup fairness, understandable explanations, meaningful human review, cybersecurity and coordinated oversight of cross-border providers. Without these conditions, data-driven lending may replace conventional credit exclusion with automated exclusion.

Limitations of the Study

The review depended on published and accessible evidence and may not capture proprietary models, internal lender experience or enforcement practice. Peer-reviewed African studies using actual SME loan and subgroup-performance data remain limited, and this low-data evidence base restricts claims about model accuracy and fairness. National definitions of SMEs, variation in digital infrastructure and differences between legal provisions and practical enforcement reduce direct country comparability. Rapid technological and regulatory changes may make some findings time-sensitive. Restriction to English-language and indexed or publicly available sources created possible language, publication and database bias. Finally, literature synthesis identified plausible relationships but could not establish causal effects or statistically validate the proposed constructs.

Directions for Future Research

Future studies should empirically test the conceptual framework with linked SME surveys, lender records and institutional data. AI capability can be measured through automation breadth, model-update frequency, predictive performance and staff competence; data quality through completeness, timeliness, representativeness and lawful provenance; safeguards through validation frequency, impact assessment, explanation quality, human-review availability and audit coverage; and SME financing outcomes through approval, price, collateral, loan size, maturity, repeat access and default. Risk should be measured through subgroup error gaps, complaint rates, breaches and model drift. Multi-item survey constructs should be assessed for reliability, convergent and discriminant validity and cross-country measurement invariance before causal relationships are estimated.

Longitudinal lender–SME panels should determine whether AI produces sustained access, affordable credit and improved business performance rather than a one-time loan. Difference-in-differences, phased model roll-outs or matched comparisons could separate the effect of AI scoring from product design and broader fintech expansion. Multilevel models should test whether digital infrastructure and regulatory maturity alter the relationship between AI capability and financing outcomes. Field experiments can compare explanation formats and human-review procedures, while fairness audits should estimate subgroup calibration and error-rate differences with adequate sample sizes. Cross-country studies should compare enforcement activity, remediation and borrower outcomes, not merely the presence of legislation.

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