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ALGORITHMIC BIAS, TRANSPARENCY, AND CONSUMER PROTECTION CHALLENGES IN ARTIFICIAL INTELLIGENCE FOR CREDIT RISK ASSESSMENT AND RESPONSIBLE LENDING

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ABSTRACT

Artificial intelligence and machine learning now shape credit decisions across origination, pricing, servicing, and collections. The paper adopts an integrative narrative review of peer reviewed finance, computer science, and legal scholarship, primary regulatory sources from the European Union, United States, United Kingdom, and Nigeria, and supervisory publications, supplemented by a critical review corpus of over 200 applied studies, largely from emerging markets. The synthesis finds that machine learning often improves default prediction and can extend credit to borrowers with thin files, but these gains are neither automatic nor evenly distributed. Bias arises from historical labels, selective outcome observation, proxy variables, and design choices, and calibration and equal error rates cannot generally be satisfied together when base rates differ. Post hoc explanations can disagree and are unstable, limiting their value for adverse action notices. Consumer protection concerns include data collection, personalised pricing, and predatory digital lending. The regulatory landscape has diverged, with the European Union deferring high risk obligations for credit scoring and the United States removing disparate impact from Regulation B. The paper proposes a conceptual model in which three risk mechanisms, moderated by lifecycle governance and regulatory context, feed back into future data, and derives six propositions for empirical testing. It concludes that responsible lending needs fairness testing, faithful

explanation, human review, and lifecycle governance beyond any single jurisdiction's minimum requirements.

KEYWORDS: Artificial Intelligence; Machine Learning; Credit Scoring; Credit Risk; Algorithmic Bias; Fair Lending; Explainable Ai; Adverse Action; Consumer Protection; Eu Ai Act; Regulation B; Responsible Lending; Conceptual Model; Emerging Markets.

1. INTRODUCTION

1.1 Background and Motivation

Credit allocation is one of the most consequential decisions a financial system makes about individuals. Whether a person can borrow, and at what price, shapes their ability to buy a home, finance education, smooth consumption through shocks, and build a business. For most of the late twentieth century, these decisions in developed markets were dominated by statistical scorecards, typically logistic regression models built on a limited set of credit bureau variables. Such models were relatively transparent and stable, but they excluded large populations with little formal credit history and left predictive signal unused.

Over the past decade, the combination of abundant data, cheap computation, and mature ML tooling has transformed this landscape. Lenders, fintech platforms, and credit bureaus now routinely deploy tree based ensembles and other non linear models, often trained on hundreds or thousands of features, including transaction data, cash flow records, device and behavioural signals, and mobile phone usage. More recently, large language models and AI agents have entered the lending workflow for document analysis, customer communication, and operational decision support. The joint Bank of England and Financial Conduct Authority survey published in October 2026 found that 86% of responding UK financial firms were using AI, with generative AI accounting for 56% of reported AI systems (Bank of England & FCA, 2026).

The same transition is visible in the applied literature from emerging markets, where reviews document the growing use of ML for credit risk and default prediction in retail, SME, and commercial lending, AI driven loan default analytics, and data driven credit decisioning and governance in corporate portfolios (Ashore-Onisemo et al., 2020; Mensah et al., 2022; Okoli et al., 2022b; Uzondu et al., 2020; Okwesa et al., 2026; Oluwo et al., 2025). Digital lending and fintech enabled transaction banking are increasingly framed as catalysts for SME growth and financial inclusion in Sub-Saharan Africa and other emerging regions (Okafor et al., 2021; Pedro et al., 2024; Agboada et al., 2022). More broadly, predictive and financial

analytics have become embedded in enterprise decision systems, forecasting, and strategic financial planning (Unamma et al., 2018b; Unamma et al., 2021b; Tonoyan et al., 2021a; Tonoyan et al., 2024b; Shah et al., 2025; Lawal & Oduleye, 2023b; Walawalkar et al., 2026; Lawal & Oduleye, 2026; Lawal & Oduleye, 2023a; Oduleye & Medon, 2023a; Agu et al., 2025; Unamma, 2022; Eboh & Aliliele, 2025b).

These developments create a familiar tension. On one side is the promise of better risk discrimination, lower losses, faster service, and inclusion of borrowers who are creditworthy but invisible to traditional models. On the other is the risk that complex models encode historical discrimination, rely on proxies for protected characteristics, defy meaningful explanation, and enable new forms of exploitation. Regulators have responded unevenly, and the year 2026 has been unusually eventful, with major changes in the European Union, the United States at both federal and state level, the United Kingdom, and emerging markets. A comprehensive and current synthesis is therefore timely.

1.2 Objectives and Research Questions

This review addresses four questions:

1. How, and with what demonstrated benefits, are AI and ML techniques being used in credit risk assessment and lending decisions?
2. What are the sources of algorithmic bias in AI credit models, what does the empirical evidence show, and how can bias be measured and mitigated?
3. What transparency and explainability approaches are available, how well do they satisfy legal duties to explain credit decisions, and where do they fall short?
4. What consumer protection challenges arise from AI driven lending, and how are regulatory and governance frameworks evolving to address them as of 2026?

1.3 Structure of the Review

The paper is organised in four main sections. Section 2 describes the research method. Section 3 presents the results and discussion: the literature synthesis across five themes (Sections 3.1 to 3.5), a conceptual model of responsible AI lending with six testable propositions (Section 3.6), a discussion of cross-cutting issues (Section 3.7), and implications for practice, policy, and theory (Section 3.8).

2. RESEARCH METHOD

This paper adopts an integrative narrative review design, which is suited to topics spanning several disciplines and combining empirical, technical, and normative literatures. Three bodies of material were examined.

- **Academic literature** in financial economics, operations research, computer science (particularly algorithmic fairness and explainable AI), and law, with emphasis on peer reviewed journal articles and leading conference proceedings, supplemented by influential working papers where peer reviewed versions were unavailable.
- **Primary legal and regulatory sources**, including statutes, regulations, court judgments, supervisory guidance, and enforcement actions in the European Union, United States, United Kingdom, and Nigeria, as published up to early November 2026.
- **Supervisory and industry evidence**, including regulator surveys, official press releases, and professional analyses used mainly to establish the timing and content of regulatory developments.
- **A curated critical review corpus** of more than 200 applied studies on banking analytics, credit and default modelling, fraud and anti-money laundering (AML) detection, AI governance, data protection, regulatory technology, and digital finance, drawn largely from African and other emerging market scholarship. These works were mapped to the review themes and are used to situate the international evidence in emerging market practice.

Sources were selected for relevance to the four research questions, methodological quality, and recency, with particular attention to developments from 2023 to 2026. The review does not claim to be a systematic review in the PRISMA sense; rather, it aims to synthesise the most significant contributions and to connect technical findings with legal and policy implications. The process involved four steps: (1) identifying core peer reviewed and legal sources for each research question; (2) mapping each source, including each critical review corpus study, to one or more of five themes (techniques and adoption, bias, transparency, consumer protection, and regulation); (3) synthesising findings thematically, noting points of agreement, tension, and gaps; and (4) abstracting the synthesis into a conceptual model (Section 3.6) whose relationships are expressed as propositions for future testing.

3. RESULTS AND DISCUSSION

This section presents the results of the review and discusses them. Sections 3.1 to 3.5 report the literature synthesis across five interrelated themes: the techniques and adoption of AI in

credit risk, algorithmic bias, transparency and explainability, consumer protection, and the regulatory and governance landscape. Each theme draws on the international peer reviewed literature, primary legal sources, and the emerging market critical review corpus described in Section 2. Section 3.6 integrates these results into a conceptual model with six propositions, Section 3.7 discusses the main cross-cutting issues, and Section 3.8 sets out implications for practice, policy, and theory.

3.1 AI in Credit Risk Assessment: Techniques and Adoption

3.1.1 From Scorecards to Machine Learning

Traditional credit scoring estimates a probability of default from applicant characteristics using logistic regression, often with variables binned into points based scorecards. These models are easy to explain and validate, satisfy monotonicity expectations (for example, more delinquencies should never improve a score), and map naturally onto the reason codes required in adverse action notices.

ML methods relax these constraints. Large benchmarking studies found that ensemble methods, especially random forests and gradient boosting, generally outperform logistic regression in classification accuracy across many credit datasets (Lessmann et al., 2015). In industry practice, gradient boosted decision trees such as XGBoost and LightGBM have become the dominant production choice for tabular credit data, while deep neural networks are used mainly for sequential transaction data, text, and images. Accuracy gains are usually modest in percentage terms, but because credit portfolios are large, small improvements in ranking ability can translate into material reductions in losses or expansions of approval rates at a given loss level.

Systematic and conceptual reviews from emerging markets reach broadly similar conclusions. ML methods are reported to improve default prediction and early warning in retail, SME, and commercial lending portfolios, and to support recovery optimisation once loans deteriorate (Ashore-Onisemo et al., 2020; Mensah et al., 2022; Okoli et al., 2022b). Related work examines advances in credit decisioning and governance for corporate portfolios, data driven risk evaluation for emerging market financial institutions, and ML in adjacent underwriting domains such as insurance (Uzondu et al., 2020; Akomolafe & Agu, 2019b; Oluwo et al., 2024). Credit models also interact with institution wide risk architecture, including asset liability management, interest rate risk, integrated enterprise risk management, capital allocation, and capital adequacy frameworks (Mensah et al., 2023; Mensah et al., 2019a; Mensah et al., 2019b), and with commercial forecasting models used by multichannel lending institutions (Dada et al., 2021b).

3.1.2 Alternative Data and Financial Inclusion

A major motivation for AI in lending is the inclusion of borrowers without conventional credit histories. Research shows that non traditional data carry real predictive information. Berg et al. (2020) found that simple digital footprint variables, such as device type and email provider, predicted default as well as or better than credit bureau scores for an e-commerce lender, and complemented them. Björkegren and Grissen (2020) showed that behaviour revealed in mobile phone usage predicts repayment in a developing country setting, which is directly relevant to markets where bureau coverage is thin. Di Maggio et al. (2022) found that a fintech lender using alternative data extended credit to so called invisible primes, borrowers whose low traditional scores understated their creditworthiness.

These findings support the inclusion argument, but they also foreshadow the risks discussed later. Many alternative variables correlate with income, ethnicity, age, or gender; some are collected through intrusive means; and borrowers are often unaware of which signals are being used. The inclusion benefit is therefore conditional on governance.

Emerging market scholarship links these possibilities to wider digital finance infrastructure. Reviews of financial inclusion and digital banking transformation in Sub-Saharan Africa, digital lending profitability, and fintech enabled SME lending highlight both the promise and the policy dilemmas of data driven credit (Agboada et al., 2022; Pedro et al., 2024; Okafor et al., 2021). Privacy focused digital identity verification is presented as a precondition for inclusion in Africa (Kumuyi et al., 2024b), while studies of web based payment adoption, blockchain enabled payments, distributed ledger interoperability, remittance liquidity, and enterprise payment gateways describe the rails through which digital credit increasingly flows (Agyei et al., 2019; Olaogun et al., 2025; Adesuyi et al., 2023; Akomolafe et al., 2023; Akomolafe et al., 2024a). Digital collections platforms operating at very large scale (Osuji et al., 2021) and bank product innovation in private banking, trade finance, relationship banking, and post-pandemic bank and capital market collaboration (Agboada et al., 2020; Agboada et al., 2018; Ezeako et al., 2019; Isiekwu et al., 2025) shape how credit is marketed, serviced, and recovered. Studies of digital inclusion, workforce readiness, and technology adoption in emerging economies (Rukh et al., 2023a; Unamma et al., 2018a; Oteri & Chibwaye, 2022), together with evidence on access to agribusiness finance, gender inclusion in African value chains, and women's leadership in African business (Michael & Ogunsola, 2019a; Michael & Ogunsola, 2022b; Ukadike & Ibeh, 2020), underline that who benefits from AI credit depends heavily on prior access to digital tools and formal economic activity.

3.1.3 Generative and Agentic AI in the Lending Lifecycle

Since 2023, generative AI has expanded the role of AI beyond scoring. Lenders use large language models to extract information from bank statements, payslips, and tax documents; to summarise applications for underwriters; to draft customer communications and adverse action letters; to power conversational assistants; and to support collections. AI agents that can take sequences of actions with limited human input are also emerging. The 2026 UK survey found that agents were widely deployed, although mostly with limited autonomy, and that oversight of third party AI systems was the most commonly reported area of governance uncertainty (Bank of England & FCA, 2026). These tools may not compute the probability of default directly, yet they can shape the data entering credit models and the information consumers receive, which brings them within the scope of responsible lending concerns.

A fast growing technical literature addresses the reliability of these systems. Work on hallucination mitigation in retrieval augmented generation, modular architectures for grounded document analysis, and natural language processing for unstructured financial and public service records is directly relevant to automated document intake in underwriting (Ajala et al., 2026; Nwakamma et al., 2026; Iziduh et al., 2020). Research on using language models as judges for automated model governance, context aware data curation for fine-tuning, and automated evaluation of sensitive content in large scale ML systems points to emerging assurance techniques (Nwakamma et al., 2024a; Oyesiji et al., 2024; Unamma et al., 2022). Security research on agentic workflows identifies threats such as prompt injection, tool poisoning, memory manipulation, and excessive agency (Nwakamma et al., 2024b), while legal analyses examine privilege and confidentiality when large language models are deployed in enterprises and propose multi-agent quality control for regulated documents (Ominyi et al., 2025c; Ominyi et al., 2025a). Organisational studies of generative AI readiness, autonomous agents, AI assisted incident analysis, AI in strategic decision making, AI driven revenue assurance, and the effect of AI on job roles complete the picture of a technology moving from pilots into core operations (Afrihyia et al., 2025; Ayinde et al., 2025; Ogundairo & Ayivi-Donkor, 2024b; Unamma et al., 2025a; Shah et al., 2025; Sakyi et al., 2023; Essandoh et al., 2025).

3.1.4 Adjacent Applications: Fraud, AML, and Transaction Monitoring

Credit risk models rarely operate in isolation. In practice they sit beside fraud detection, anti-money laundering, and transaction monitoring systems that share data, infrastructure, and governance, and whose errors can also deny people access to credit. Reviews document advances in ML for financial fraud detection in banking, data mining techniques for fraud,

predictive analytics for AML, and anomaly detection in financial time series (Atakpa & Abetoh, 2022; Unamma et al., 2021a; Atakpa, 2021; Atakpa & Fobellah, 2023; Okwesa et al., 2020). Applied models address synthetic identity fraud, adaptive real-time fraud risk scoring, SME fraud monitoring, AI driven fraud detection in UK digital payments, and AI supported financial crime investigation (Elebe et al., 2023; Fadayomi et al., 2024; Hammed et al., 2026; Bello et al., 2025c; Okoruwa et al., 2025). Integrated cybersecurity and AML governance, blockchain supported know your customer (KYC) and AML processes, AML and anti-bribery regimes, correspondent banking controls, and VoIP forensics for fraud and compliance monitoring illustrate the convergence of fraud, compliance, and security functions (Fadayomi et al., 2021; Bello et al., 2025a; Ominyi & Anichukwueze, 2021; Okafor et al., 2024a; Mbonu et al., 2021).

Further work applies AI risk scoring and fraud detection to cross-border payments (Adesuyi et al., 2024; Adesuyi et al., 2025a), AI assisted compliance monitoring and anomaly detection in high volume transaction environments (Ominyi et al., 2024a), and predictive analytics for fraud prevention in public systems (Adelanwa et al., 2023b). Studies on fraud in healthcare payments and donor funded programmes, healthcare financial analytics, cyber-enabled fraud in telemedicine, and venture capital and private equity investment fraud show that the same techniques, and the same risks of false positives and opaque scoring, recur across sectors (Atakpa et al., 2024; Abetoh & Atakpa, 2022; Abetoh & Atakpa, 2024; Atakpa et al., 2026; Ekechi et al., 2022; Eboh & Aliliele, 2023; Eboh & Aliliele, 2024; Eboh & Aliliele, 2025a). For responsible lending, the lesson is that consumer protection reviews should cover the full decision pipeline, including fraud and identity screens that may reject applicants before any credit score is computed.

3.1.5 Summary of Techniques

Table 1. Principal AI and ML approaches used in credit risk assessment.

Approach	Typical use in lending	Main strengths	Main risks
Logistic regression and scorecards	Application and behavioural scoring; regulatory benchmark models	Transparent, stable, easy to validate and to generate reason codes	Lower predictive power; limited use of complex data
Tree ensembles (random forest, gradient boosting)	Production scoring, pricing, fraud, early warning	High accuracy on tabular data; handles non linearity and interactions	Opacity; proxy discrimination through interactions; explanation instability

Approach	Typical use in lending	Main strengths	Main risks
Neural networks and deep learning	Transaction sequences, text, images, cash flow underwriting	Learns representations from raw and unstructured data	Very low interpretability; data hungry; drift sensitive
Interpretable ML (GAMs, explainable boosting, monotonic constraints)	Scoring where explanation is critical	Near ensemble accuracy with built in interpretability	Requires more design effort; may still use proxies
Generative AI (large language models)	Document processing, communications, underwriting support	Handles unstructured information at scale	Hallucination, inconsistency, privacy leakage, weak auditability
Agentic AI	Workflow automation in servicing and collections	Efficiency across multi step processes	Accountability gaps; limited supervisory guidance

Source: author synthesis of the literature reviewed.

3.2 Algorithmic Bias in Credit Decisions

3.2.1 Sources of Bias

Algorithmic bias in credit refers to systematic and unjustified differences in outcomes or errors across groups, particularly groups defined by legally protected characteristics such as race, ethnicity, sex, age, religion, national origin, or marital status. Bias can enter at every stage of the model lifecycle.

- **Historical and label bias.** Models learn from past lending outcomes shaped by discrimination, redlining, and unequal economic opportunity. Default labels may themselves reflect unequal treatment, for example higher prices charged to some groups that make default more likely.
- **Selective labels.** Repayment outcomes are only observed for applicants who were approved, so models trained on accepted loans may be miscalibrated for groups that were historically rejected (Lakkaraju et al., 2017).
- **Representation and measurement bias.** Groups with thin files or less formal financial activity are under represented or measured with more noise, which degrades model accuracy for them (Blattner & Nelson, 2021).

- **Proxy discrimination.** Even when protected attributes are excluded, flexible models can reconstruct them from correlated variables such as postcode, shopping patterns, educational institution, or device characteristics. Removing the protected attribute, sometimes called fairness through unawareness, does not prevent this.
- **Design and objective choices.** Decisions about target definition, performance metrics, feature selection, and cut off thresholds embed value judgements that can disadvantage groups even when the model is statistically sound.
- **Feedback loops.** Denials and adverse pricing can worsen the financial position of affected groups, which then appears in future training data as confirmation of higher risk.
- **Human and data pipeline bias.** Human judgement enters through labelling, overrides, and policy rules; research on cognitive biases in financial decision making and in cross-functional decisions shows how such judgements can be systematically skewed (Fobellah, 2025a; Ebisi et al., 2023). Weaknesses in data migration, validation, and governance in high volume financial operations, and the absence of a single source of truth across reporting systems, can also introduce errors that fall unevenly on different groups (Okeke et al., 2023; Okwesa & Ashore-Onisemo, 2023; Unamma et al., 2019a).

3.2.2 Empirical Evidence

The empirical record is nuanced: AI does not uniformly increase or decrease discrimination. Bartlett et al. (2022) studied US mortgage lending and found that Latinx and African American borrowers paid higher interest rates than comparable borrowers, with the gap smaller for algorithmic fintech lenders than for face to face lending, though not eliminated. This suggests algorithms can reduce some forms of taste based discrimination while still producing disparities through pricing strategies that exploit differences in shopping behaviour.

Fuster et al. (2022) showed that moving from a traditional logistic model to a more flexible ML model in mortgage lending increased overall predictive accuracy, but the benefits were unevenly distributed. Because flexible models can better triangulate group membership from correlated features, they increased dispersion in predicted risk within and across groups, with some minority borrowers made worse off. Blattner and Nelson (2021) found that credit scores are statistically noisier for minority and low income borrowers because of thinner histories, implying that a part of observed disparities stems from data quality rather than model form, and that better models alone cannot fully fix the problem.

More recent studies extend these findings to gender and to other markets. Stancu (2025), using Romanian credit register data over seven years, compared ML models with traditional methods to examine gender bias in mortgage credit scoring and highlighted that accuracy gains from ML do not automatically translate into fairer outcomes. A 2026 audit of a widely used Taiwanese credit default dataset reported that gender information leaked through proxy variables even after explicit protected attributes were removed and standard fairness audits were passed, challenging the assumption that blindness is sufficient (Navya et al., 2026). A 2025 systematic review in the *Journal of Risk and Financial Management* found that most fairness studies in credit relied on legacy benchmark datasets such as the German Credit data and that none applied causal inference techniques, raising questions about external validity (Towards fair AI, 2025).

A complementary strand of applied work emphasises structured auditing. A review of fairness and bias auditing of decision models in credit and service delivery sets out audit practices that can be adapted to lending (Unamma & Ashore-Onisemo, 2023), while research on energy load forecasting shows that a model can be accurate yet produce inequitable outcomes across districts, a pattern directly analogous to credit (Komi, 2023). Studies of bias and spoofing countermeasures in facial recognition, which matters for digital identity checks at onboarding, and of bias in multi-touch attribution models demonstrate that bias arises across the data products surrounding credit decisions (Adeniyi et al., 2025; Sanni et al., 2022a). Work on ethical AI adoption, comparative AI governance, and quantitative evaluation of diversity and inclusion investments (Osinem et al., 2025b; Afrihyia et al., 2024a; Uchechi et al., 2022b), and on intersectionality and inclusion (Lilian et al., 2025a), supports moving beyond single attribute analyses.

Enforcement experience illustrates how these mechanisms occur in practice. In July 2025, the Massachusetts Attorney General announced a $2.5 million settlement with Earnest Operations, a student loan lender, alleging that its AI underwriting models created risks of disparate harm to Black, Hispanic, and non-citizen applicants. The allegations included a failure to test models for disparate impact, the use of a Cohort Default Rate variable tied to the educational institution attended, a knockout rule based on immigration status, and inaccurate adverse action notices. Earnest denied the allegations but agreed to stop using those variables and to implement an AI governance programme with fairness testing (Massachusetts Attorney General, 2025). The case shows how an apparently neutral institutional variable can operate as a proxy and how bias, explanation failures, and governance weaknesses tend to appear together.

3.2.3 Measuring Fairness

Fairness in credit has no single definition, and the choice of metric is a normative decision. Table 2 summarises the main families of metrics used in research and practice.

Table 2. Common fairness metrics applied to credit models.

Metric	Definition (simplified)	Interpretation in lending	Limitations
Demographic parity / adverse impact ratio	Approval rates equal across groups; ratio of group approval rates (four fifths rule as a screening heuristic)	Equal access to credit regardless of group	Ignores genuine risk differences; may conflict with safety and soundness
Equal opportunity	Equal true positive rates (creditworthy applicants approved at equal rates)	Good borrowers have equal chances of approval in every group	Requires reliable outcome labels, which are missing for rejected applicants
Equalised odds	Equal true positive and false positive rates	Errors are distributed equally across groups	Often cannot be met jointly with calibration
Predictive parity and calibration	A given score means the same default probability in every group	Prices and decisions reflect risk consistently	Can coexist with large approval gaps
Individual fairness	Similar applicants receive similar outcomes	Consistency at the case level	Requires a defensible similarity measure
Counterfactual fairness	Outcome unchanged if protected attribute were different, holding causal structure fixed	Addresses proxy pathways directly	Needs a credible causal model, rarely available

Sources: Hardt et al. (2016); Kleinberg et al. (2017); Chouldechova (2017); Barocas et al. (2023); Kozodoi et al. (2022).

A central theoretical result is that, when base rates of default differ between groups, calibration and equal error rates cannot generally be satisfied simultaneously (Kleinberg et al., 2017; Chouldechova, 2017). Lenders and regulators must therefore decide which notion of fairness takes priority in a given context. Hurlin et al. (2021) propose formal statistical tests of fairness for credit scoring models and methods to identify the variables responsible for unfairness, which helps translate abstract metrics into model governance practice.

3.2.4 Bias Mitigation Approaches

Mitigation techniques are commonly classified by where they intervene in the modelling pipeline.

- **Pre-processing** methods alter the training data, for example through reweighting, resampling, or transforming features to remove information about protected attributes.
- **In-processing** methods change the learning objective, adding fairness constraints or adversarial components that penalise the model for predicting group membership.
- **Post-processing** methods adjust scores or thresholds after training, for example group specific cut offs, which may be legally problematic where they involve explicit differential treatment.
- **Search for less discriminatory alternatives (LDAs).** Because many models achieve near identical accuracy (the so called Rashomon effect), lenders can search the space of comparable models for one with smaller disparities. This approach aligns well with the traditional legal framework for disparate impact.

Kozodoi et al. (2022) evaluated a range of fairness processors on credit data and found that meaningful reductions in unfairness are often achievable at modest cost to profit, although the trade off depends on the metric and dataset. Bono et al. (2021) emphasise that the costs and benefits of fairness interventions fall on different groups and that policy choices should be explicit. A practical obstacle is that lenders often lack protected attribute data: in the United States, creditors are generally prohibited from collecting race and ethnicity outside mortgage lending, so fairness testing relies on statistical proxies such as Bayesian Improved Surname Geocoding, which introduces measurement error of its own. Gillis (2022) argues that focusing on which inputs a model uses, rather than on its outcomes, is a fallacy in the ML context, because excluding variables neither guarantees fairness nor reveals proxy effects.

Privacy preserving approaches offer partial answers to the data access problem. Federated learning has been proposed for secure cross-organisational data management (Sanni et al., 2023), and work on disagreement in human in the loop federated ML highlights the governance questions that arise when several parties train models jointly (Ladapo et al., 2026). Bias auditing frameworks (Unamma & Ashore-Onisemo, 2023) and analyses of automated decision making under US anti-discrimination law (Annan, 2025a) stress that mitigation must be documented in a way that withstands legal and supervisory review.

3.2.5 The Shifting Legal Basis for Bias Testing

Bias testing in US credit has historically rested on two theories of discrimination under the Equal Credit Opportunity Act (ECOA): disparate treatment and disparate impact (the effects test). This foundation changed in 2026. On 22 April 2026, the Consumer Financial Protection Bureau (CFPB) published a final rule amending Regulation B to remove the effects test and state that ECOA does not authorise disparate impact liability; the rule also narrowed the discouragement prohibition and restricted special purpose credit programmes, taking effect on 21 July 2026 (CFPB, 2026). The rule is being challenged in federal court by fair housing organisations, and it does not affect disparate impact liability under the Fair Housing Act or state law analogues. Disparate treatment, including the intentional use of facially neutral variables as proxies for protected characteristics, remains prohibited.

For AI lending, the practical significance is twofold. Federal supervisory pressure to search for less discriminatory alternatives has weakened, but legal exposure has not disappeared, because state laws, the Fair Housing Act for mortgage lending, private litigation, and foreign regimes such as the EU AI Act still require or reward outcome based testing. The divergence also creates long term uncertainty for lenders whose models and controls are built to operate across administrations and jurisdictions. Legal scholarship on automated decision making and anti-discrimination compliance under US law, and on the tension between algorithmic accountability and trade secret protection, frames these choices (Annan, 2025a; Annan, 2024), and reviews of algorithmic accountability and model risk management in financial services argue that outcome testing remains a core control regardless of the liability theory in force (Ominyi & Anichukwueze, 2023).

3.3 Transparency and Explainability

3.3.1 Why Transparency Matters in Credit

Transparency serves several distinct audiences and purposes. For consumers, explanations make it possible to understand a decision, correct errors, and improve future applications. For lenders, interpretability supports model validation, debugging, and detection of spurious or discriminatory relationships. For supervisors and courts, documentation and explanation enable accountability. For society, transparency underpins trust in automated decision making. These purposes call for different kinds of explanation: a global description of how the model works, a local explanation of a single decision, or actionable guidance on what an applicant could change.

3.3.2 Explainability Methods

Two broad strategies exist. The first is to use models that are interpretable by design. Rudin (2019) argues forcefully that for high stakes decisions, practitioners should prefer inherently interpretable models rather than explaining black boxes after the fact, noting that in many tabular settings interpretable models perform comparably. In credit, this includes scorecards, generalised additive models and explainable boosting machines (Lou et al., 2012; Nori et al., 2019), and gradient boosting with monotonicity constraints. The second strategy is post hoc explanation of complex models, using methods such as SHAP (Lundberg & Lee, 2017), LIME (Ribeiro et al., 2016), partial dependence, and counterfactual explanations (Wachter et al., 2018).

Applied studies extend these ideas into financial operations. Explainable AI architectures for marketing automation in healthcare and financial applications, and interpretable ML for early failure prediction, illustrate how interpretability can be designed into production systems (Sanni et al., 2026; Komi & Adamolekun, 2021). Reviews of human in the loop decision systems and human in the loop ML show how explanation and human review work together in practice, particularly where model confidence is low or stakes are high (Ashore-Onisemo et al., 2025; Ladapo et al., 2022).

Table 3. Explainability approaches and their suitability for lending.

Method	Scope	Use in lending	Key limitations
Interpretable models (scorecards, GAMs, explainable boosting)	Global and local	Primary decision models where explanation is legally required	Design effort; possible small accuracy loss
Monotonic constraints	Global	Ensures intuitive direction of effects in ensembles	Does not by itself produce reason codes
SHAP (Shapley additive explanations)	Local and aggregated global	Ranking principal reasons for adverse action; model validation	Sensitive to correlated features and baseline choice; computational cost
LIME (local surrogate models)	Local	Exploratory diagnosis	Instability across runs; vulnerable to manipulation
Counterfactual explanations and recourse	Local	Telling applicants what changes would alter the outcome	Can suggest infeasible or non actionable changes; may reveal model logic

Method	Scope	Use in lending	Key limitations
Partial dependence and accumulated local effects	Global	Validation and documentation	Averaging hides heterogeneity; misleading with correlated inputs

Sources: Lundberg & Lee (2017); Ribeiro et al. (2016); Wachter et al. (2018); Ustun et al. (2019); Rudin (2019).

3.3.3 Limits of Post Hoc Explanation

Post hoc methods are widely used to generate adverse action reasons from complex models, but they have well documented weaknesses. Different explanation methods often disagree about which features matter most for the same prediction (Krishna et al., 2022). Explanations can be unstable to small perturbations and can be deliberately manipulated, so that a biased model appears to rely on innocuous features (Slack et al., 2020), a practice sometimes called fairwashing. When features are highly correlated, as is common in credit data, attribution may be spread across proxies in ways that obscure the true driver. Counterfactual explanations raise the additional question of actionable recourse: telling an applicant that a higher age or a different postcode would change the outcome is not useful and may be offensive (Ustun et al., 2019). Finally, explanations aimed at consumers must be comprehensible, and there is limited evidence on whether technically faithful explanations actually help borrowers understand or contest decisions. Related governance work notes that disagreement among models and participants in human in the loop and federated settings, and the biases of automated evaluators such as language models used as judges, can undermine confidence in explanation pipelines (Ladapo et al., 2026; Nwakamma et al., 2024a).

3.3.4 Legal Duties to Explain Credit Decisions

United States: adverse action notices.

Under ECOA and Regulation B, creditors must give applicants who suffer adverse action a statement of the specific principal reasons, and the Fair Credit Reporting Act imposes related notice duties when consumer report information is used. In Circular 2022-03, the CFPB stated that these duties apply regardless of the complexity of the technology used. Circular 2023-03 added that creditors cannot simply select the closest items from the sample form checklist if those do not accurately describe the factors actually considered, which is particularly important when models use data that consumers would not expect to be relevant (CFPB, 2022, 2023). Translating a complex model into a small number of truthful, specific,

and intelligible reasons is therefore a legal requirement, not merely good practice. The Earnest settlement, which included allegations of inaccurate adverse action notices, shows that explanation failures can attract enforcement independent of bias findings.

The trade secret question is not unique to the United States. Analyses of algorithmic accountability and trade secret protection (Annan, 2024), of global marketing law and consumer protection compliance (Anichukwueze et al., 2019), and of responsible AI governance for automated decision systems in regulated industries (Ominyi & Anichukwueze, 2024) converge on the view that confidentiality claims cannot defeat a consumer's right to a meaningful reason.

European Union: GDPR, case law, and consumer credit.

In the EU, Article 22 of the General Data Protection Regulation (GDPR) restricts decisions based solely on automated processing that significantly affect individuals, while Articles 13 to 15 require meaningful information about the logic involved. Two judgments of the Court of Justice of the European Union (CJEU) have given these provisions particular force in credit. In *SCHUFA* (C-634/21, December 2023), the Court held that the automated generation of a credit score can itself constitute an automated decision where a third party draws strongly on it in deciding whether to contract. In *Dun & Bradstreet Austria* (C-203/22, February 2025), it held that a person subject to an automated credit assessment is entitled to an explanation of the procedure and principles actually applied that enables them to understand and contest the decision; merely communicating a complex algorithm is insufficient, and trade secret claims must be weighed by a court or supervisory authority rather than used as a blanket refusal (CJEU, 2025).

The revised Consumer Credit Directive (EU) 2023/2225, which applies from 20 November 2026, adds credit specific rights. Where creditworthiness assessment involves automated processing of personal data, consumers may request human intervention, including a clear and comprehensible explanation of the assessment, the opportunity to express their point of view, and a review of the decision. The directive also extends coverage to small loans and buy now pay later products. The EU AI Act separately provides a right to an explanation of individual decisions taken on the basis of high risk AI systems, which will become relevant for credit scoring once the high risk regime applies (see Section 3.5.1).

3.3.5 Auditability and Assurance

Explanation to consumers is complemented by assurance to boards, auditors, and supervisors. Conceptual reviews examine how auditors should approach AI powered financial systems, how responsible AI can be embedded in IT auditing through evidence validation and human

oversight, and how AI assisted continuous auditing can strengthen technology risk oversight (Fobellah, 2025b; Elebe & Anunagba, 2025; Aliliele et al., 2025a). Related frameworks address AI enabled IT general controls and SOX audit automation, data analytics for audit quality in financial institutions, predictive models for financial statement validation, and security audit and enterprise risk assessment (Mbonu et al., 2022; Ozowara et al., 2025; Okoli et al., 2022a; Dosunmu & Ogundele, 2019). Technology enabled internal audit and risk based audit models (Akomolafe & Agu, 2018; Akomolafe et al., 2023a) provide a natural home for periodic review of credit models, their fairness metrics, and the accuracy of the reasons they generate.

3.4 Consumer Protection Challenges

Bias and opacity are the most studied risks of AI lending, but consumer protection concerns extend further. This section reviews seven challenges that recur in the literature and in enforcement.

3.4.1 Data Collection, Privacy, and Surveillance

AI models reward more data, which creates an incentive to collect information that consumers would not expect to be used in credit decisions, from browsing and purchasing behaviour to phone contacts and location histories. Hurley and Adebayo (2016) warned early that big data credit scoring could undermine accuracy, privacy, and the ability of consumers to understand and correct the information used about them. The CFPB has noted that some AI models rely on data harvested from consumer surveillance or not typically found in credit files. Data minimisation principles in the GDPR and similar laws, and specific limits in sector rules, are therefore important safeguards.

A substantial applied literature translates these principles into architecture and governance. Proposed models include privacy preserving data architectures for regulated analytics under GDPR and HIPAA, frameworks for harmonising compliance across the GDPR, Nigeria's data protection regime, and US privacy laws, and data privacy governance for cross-border digital platforms (Atakpa & Abolaji, 2022; Ominyi & Anichukwueze, 2022a; Annan, 2022). Reviews compare data protection regulations and secure cloud strategies across jurisdictions, assess data protection impact assessment models for multi-cloud financial infrastructure, and propose legal and ethical risk modelling for enterprise data protection (Mbonu et al., 2019; Mbonu et al., 2022a; Mbonu et al., 2018). Data sensitivity classification with regulatory traceability, data lakehouse governance for loss prevention, privacy by design in corporate transactions and in role based security for sensitive personal data, and privacy centric security engineering offer implementable controls (Aliliele et al., 2024a; Aliliele et al., 2025b;

Ominyi, 2021; Badmus et al., 2024; Okoruwa et al., 2020). Comparative work on privacy preserving health data governance, AI governance and privacy compliance in digital health, trust and privacy in AI powered remote monitoring, and data governance frameworks in digital learning systems shows that similar challenges arise wherever sensitive personal data feed AI decisions (Afrihyia et al., 2024b; Ekechi et al., 2026; Akintola et al., 2025; Orise & Niniola, 2025). On-device privacy, zero knowledge storage, and privacy preserving edge models suggest technical routes to reduce data collection by mobile lending apps (Oyesiji et al., 2026; Nwakamma et al., 2025), while research on customer data platforms in emerging market banking stresses that customer trust depends on how such data are governed (Ukadike, 2022).

3.4.2 Accuracy, Errors, and Contestability

Errors in input data, from credit reports, data brokers, or automated document extraction, can propagate through models to produce wrong decisions. As models incorporate more data sources, it becomes harder for consumers to know which records were used and to dispute them. Contestability requires not only explanation but also accessible processes for correction and human review, which is why the EU Consumer Credit Directive and several US state laws emphasise appeal and review rights. Studies of digital complaint resolution systems for public accountability, single source of truth frameworks for inter-agency reporting, predictive compliance monitoring based on consumer complaint data, predictive analytics in public financial oversight, and NLP for unstructured records suggest how complaints and disputes can be turned into systematic signals of model error (Unamma et al., 2019b; Unamma et al., 2019a; Adeyelu, 2018; Ashore-Onisemo & Unamma, 2022b; Iziduh et al., 2020). Research on data integrity during migration and on auditability in high volume financial operations underlines that contestability depends on reliable records (Okeke et al., 2023; Okwesa & Ashore-Onisemo, 2023).

3.4.3 Personalised Pricing and Exploitation of Vulnerability

AI enables highly granular pricing and marketing. While risk based pricing is legitimate, models can also price according to a borrower's predicted willingness to pay or likelihood of shopping around, which can disadvantage less sophisticated or more constrained borrowers. Bartlett et al. (2022) suggest that pricing disparities in algorithmic lending may partly reflect differences in shopping behaviour. Behavioural signals can also identify financially stressed or vulnerable consumers, who might then be targeted with high cost credit rather than protected. Responsible lending requires that predictive capacity be used to identify affordability concerns, not to exploit them.

The marketing analytics literature shows how quickly these capabilities are maturing. Studies describe predictive customer journey analytics for cross-sell and upsell in financial services, ML for customer acquisition and retention, audience segmentation and forecasting, and predictive segmentation in regulated professional services (Ukadike & Ibeh, 2023; Ogundairo & Ayivi-Donkor, 2023a; Basnet et al., 2021; Atima et al., 2022). Others address marketing return on investment in regulated services, CRM adoption and revenue analytics in financial services firms, digital transformation in capital markets, analytics driven go to market strategies under compliance constraints, and the embedding of economic evaluation algorithms into data pipelines (Sanni et al., 2020a; Okoli et al., 2025; Sanni & Attah, 2023a; Sanni & Atima, 2021a; Ogundairo & Ayivi-Donkor, 2023b). Work on adaptive control of AI driven marketing automation in financial compliance environments, marketing analytics for governance, risk, and compliance decisions, global marketing law and consumer protection, and ethics and compliance training (Sanni et al., 2022b; Sanni, 2026c; Anichukwueze et al., 2019; Anichukwueze et al., 2020) indicates that the boundary between personalisation and exploitation must be policed through governance, not left to model objectives alone.

3.4.4 Predatory Digital Lending in Emerging Markets

In many emerging markets, smartphone based lending apps have expanded access to small, short term loans, often using automated scoring based on phone data. This expansion has been accompanied by documented abuses, including excessive charges, harvesting of contact lists, and debt collection through harassment and public shaming of borrowers to their contacts. Nigeria offers a clear example of regulatory response. The Federal Competition and Consumer Protection Commission (FCCPC) issued the Digital, Electronic, Online, or Non-Traditional Consumer Lending Regulations 2025, effective 21 July 2025, replacing a 2022 interim framework. The regulations require registration of digital lenders, upfront disclosure of interest, fees, and repayment terms, compliance with the Nigeria Data Protection Act 2023, explicit limits on app access to contacts, call logs, and photo galleries, and periodic monitoring of interest rates to ensure they are not exploitative (FCCPC, 2025). The Nigerian experience illustrates that in many markets the most urgent AI lending harms concern data abuse and collection conduct as much as model fairness. Assessments of cyber risk maturity against Nigeria's insurance and data protection rules, harmonisation of the Nigerian regime with the GDPR and US privacy laws, and studies of digital lending and high volume collections platforms provide useful context for implementing these rules (Fadero et al., 2021; Ominyi & Anichukwueze, 2022a; Okafor et al., 2021; Pedro et al., 2024; Osuji et al., 2021).

3.4.5 Risks Specific to Generative and Agentic AI

Generative AI introduces new failure modes. Language models can produce fluent but incorrect statements about loan terms or a customer's rights, extract figures incorrectly from documents, or give inconsistent answers to similar customers. When used to draft adverse action reasons, they may generate plausible language that does not reflect the factors actually used by the scoring model, which would breach the accuracy requirement discussed in Section 3.3.4. Agentic systems acting across several steps raise accountability questions about who approved each action. Supervisory guidance has not kept pace: the US interagency model risk guidance issued in April 2026 explicitly placed generative and agentic AI outside its scope as novel and rapidly evolving, leaving institutions to govern them through broader risk management practices (Federal Reserve et al., 2026). The applied literature offers some building blocks for that broader governance, including hallucination mitigation, LLM based evaluation, agent security controls, and governance of sensitive content in large ML systems (Ajala et al., 2026; Nwakamma et al., 2024a; Nwakamma et al., 2024b; Unamma et al., 2022), as well as analyses of privilege and confidentiality in enterprise LLM deployment (Ominyi et al., 2025c).

3.4.6 Third Party Dependence and Concentration

Many lenders, especially smaller banks and fintechs, rely on vendor models, data providers, and foundation model providers. This creates information asymmetries: the deploying lender remains legally responsible for fair lending and adverse action compliance but may have limited insight into the vendor's training data or features. The 2026 UK survey identified oversight of third party AI as the leading governance challenge and noted the growing materiality of third party systems (Bank of England & FCA, 2026). Concentration on a few providers also creates the possibility of correlated errors or biases across many lenders simultaneously, a systemic dimension of algorithmic monoculture.

Studies of vendor risk assessment, API governance in financial institutions, risk based business intelligence for fintech platforms, and cloud identity, access, and misconfiguration management describe controls that apply directly to AI supply chains (Tonoyan et al., 2024a; Aliliele et al., 2023b; Mbonu et al., 2021a; Mbonu et al., 2020; Aliliele et al., 2023a). Evidence from cloud migration at a South African retail bank, infrastructure as code governance, and AI augmented secure software engineering highlights the technical dependencies beneath credit platforms (Ladapo et al., 2025; Mbonu et al., 2020b; Odejobi et al., 2025). Resilience frameworks for global payment infrastructure, operational resilience in financial services, and business continuity in African financial services (Adesuyi et al.,

2025b; Ashore-Onisemo & Unamma, 2022a; Fadero et al., 2020), together with research on risk based cybersecurity assurance, cyber risk quantification, board level cyber governance, and cybersecurity risk management for financial institutions (Fadayomi et al., 2019; Dosunmu & Ogundele, 2024b; Dosunmu & Ogundele, 2025b; Bello et al., 2024), show how third party AI failures can become operational and conduct failures at once. Work on AI in cybersecurity and on cybersecurity compliance as a source of competitive advantage (Hussain & Adebayo, 2026; Annan, 2025b) suggests that strong controls can also be a market differentiator.

3.4.7 The Inclusion Paradox

AI can both expand and restrict access. Alternative data can bring creditworthy but invisible borrowers into the formal system (Di Maggio et al., 2022), yet flexible models can also sort borrowers more finely, raising prices or denying credit to groups previously pooled with lower risk applicants (Fuster et al., 2022). Whether the net effect is inclusive depends on market structure, competition, pricing practices, and regulation. Policy should therefore evaluate inclusion claims empirically rather than accepting them as an inherent property of AI. Reviews of financial inclusion and digital banking in Sub-Saharan Africa, privacy focused digital identity, and digital inclusion through analytics partnerships (Agboada et al., 2022; Kumuyi et al., 2024b; Rukh et al., 2023a) make the same point: inclusion outcomes depend on infrastructure, policy, and governance as much as on algorithms.

3.5 The Regulatory and Governance Landscape in 2026

Regulation of AI in lending combines general AI laws, sector specific consumer credit and anti-discrimination law, data protection law, and prudential model risk guidance. This section surveys the position as of November 2026 in the jurisdictions most influential for the literature, together with an emerging market example.

3.5.1 European Union

The EU AI Act (Regulation (EU) 2024/1689) classifies AI systems used to evaluate the creditworthiness of natural persons or establish their credit score as high risk under Annex III, with an exception for fraud detection. High risk obligations include a risk management system, data governance and bias examination, technical documentation, logging, transparency to deployers, human oversight, and accuracy and robustness. Deployers that are bodies providing credit scoring must also carry out a fundamental rights impact assessment.

These obligations were originally due to apply on 2 August 2026. Following the Digital Omnibus on AI, which received final Council approval on 29 June 2026 and entered into force in late July 2026, the application date for stand alone Annex III high risk systems,

including credit scoring, was deferred to 2 December 2027, while obligations for high risk AI embedded in regulated products moved to 2 August 2028. Prohibited practices (since February 2025), general purpose AI obligations (since August 2025), and the Article 50 transparency duties and penalty regime (from August 2026) were not delayed. The deferral changes the pace of the high risk regime, not its scope.

In the meantime, other EU instruments already bite on AI credit. The GDPR and the CJEU judgments in *SCHUFA* and *Dun & Bradstreet Austria* establish rights concerning automated credit decisions and explanations. The revised Consumer Credit Directive applies from 20 November 2026, with rights to human intervention, explanation, and review where creditworthiness assessment is automated. The European Banking Authority's guidelines on loan origination and monitoring (EBA, 2020) already require institutions using automated models for creditworthiness assessment to understand them, manage model risk, and guard against bias. A systematic review of organisational readiness for the EU AI Act in multinational enterprises finds that preparation varies widely (Ominyi et al., 2024b), and comparative work on GDPR alignment and cross-jurisdiction data protection underscores the interaction between AI and data protection obligations for lenders operating in several markets (Ominyi & Anichukwueze, 2022a; Mbonu et al., 2019).

3.5.2 United States: Federal Level

The US has no general federal AI statute applicable to lending. Instead, AI credit is governed by ECOA and Regulation B, the Fair Credit Reporting Act, the Fair Housing Act, prohibitions on unfair, deceptive, or abusive acts and practices, and prudential supervision. Two federal developments in 2026 are particularly significant.

- **Regulation B amendments.** As discussed in Section 3.2.5, the CFPB's April 2026 final rule removed disparate impact from Regulation B effective 21 July 2026, narrowed discouragement, and restricted special purpose credit programmes. The CFPB had already stated that it no longer used disparate impact in supervision and enforcement. Adverse action notice duties, including the expectations set out in Circulars 2022-03 and 2023-03, remain part of the legal framework.
- **Model risk management.** On 17 April 2026, the Federal Reserve, OCC, and FDIC issued revised interagency guidance (SR 26-2; OCC Bulletin 2026-13) replacing SR 11-7, which had governed bank model risk management since 2011. The new guidance preserves the core architecture of development, validation, monitoring, and governance but adopts a more risk

based, materiality focused approach. Traditional ML credit models remain within scope, whereas generative and agentic AI are expressly excluded (Federal Reserve et al., 2026).

The combined effect is a federal framework that continues to require accurate explanations and sound model governance but places less emphasis on outcome based fairness testing and offers no specific guidance for generative AI in lending. Reviews of algorithmic accountability and model risk management in financial services, of anti-discrimination compliance for automated decisions under US law, and of harmonised risk governance and compliance for future-ready banking (Ominyi & Anichukwueze, 2023; Annan, 2025a; Okafor et al., 2024b) suggest that institutions are likely to retain broader controls than the federal floor now requires.

3.5.3 United States: State Level

States have become the more active locus of AI lending oversight, though in divergent directions. Massachusetts demonstrated in the 2025 Earnest settlement that existing consumer protection and fair lending statutes can be used to address AI underwriting without any AI specific law. Attorneys General in California, Oregon, and New Jersey have issued guidance on AI related discrimination, including in credit.

Colorado's trajectory illustrates the instability of state AI legislation. Its 2024 Artificial Intelligence Act (SB 24-205), the first comprehensive US state law on high risk AI including lending, was postponed from February to June 2026. In April 2026 a federal court temporarily blocked its enforcement, and on 14 May 2026 the governor signed SB 26-189, which repealed and replaced the 2024 Act with a narrower framework focused on automated decision making technology, emphasising notice, disclosure, appeals, and recordkeeping, enforced exclusively by the Attorney General and effective 1 January 2027. The Attorney General's proposed implementing rules were open for comment until late October 2026. For lenders operating nationally, the result is a patchwork of state requirements that may be more demanding than federal law in some respects.

3.5.4 United Kingdom

The UK has continued a principles based and sector led approach rather than adopting a horizontal AI statute. The FCA's Consumer Duty requires firms to deliver good outcomes for retail customers, including fair value and support for vulnerable customers, which applies directly to AI driven pricing and underwriting. Equality law, UK data protection law (including provisions on automated decision making), and prudential expectations on model risk complete the framework. The 2026 Bank of England and FCA survey reported widespread AI adoption, formal AI governance arrangements at most respondents, and

identified data protection and third party risk as the most significant perceived risks, with 42% of respondents considering UK data protection requirements a high compliance burden (Bank of England & FCA, 2026).

3.5.5 Emerging Markets: The Case of Nigeria

In many emerging markets, digital lending has grown faster than regulatory capacity. Nigeria's 2025 digital lending regulations (Section 3.4.4), alongside the Nigeria Data Protection Act 2023 and Central Bank of Nigeria licensing requirements, illustrate a model in which consumer protection and data protection agencies regulate conduct and data use directly, rather than through AI specific rules. Such frameworks address the most visible harms, such as harassment and intrusive data collection, but generally say little about algorithmic fairness or explanation of automated decisions. As AI scoring spreads across African and Asian credit markets, this gap is likely to become more important. Regional scholarship has begun to address it from several angles: cyber risk and data protection maturity in Nigerian financial services (Fadero et al., 2021), harmonisation of the Nigerian data protection regime with the GDPR and US laws (Ominyi & Anichukwueze, 2022a), regulatory clearance and post-merger compliance in African and multi-jurisdictional banking (Ominyi & Anichukwueze, 2020; Ominyi, 2020), digital trade regulation between the United States and Nigeria, technology transfer compliance under export controls, and AI driven compliance advisory services for SMEs (Jones & Ominyi, 2024b; Jones & Ominyi, 2023; Jones & Ominyi, 2025a).

3.5.6 International Standards and Soft Law

Voluntary frameworks increasingly inform practice across jurisdictions. The NIST AI Risk Management Framework 1.0 (NIST, 2023) organises AI risk management around governing, mapping, measuring, and managing risks, including harmful bias. ISO/IEC 42001:2023 specifies requirements for AI management systems. The OECD AI Principles promote fairness, transparency, and accountability. These instruments are frequently used to fill gaps left by binding rules, for example in governing generative AI outside the scope of US model risk guidance.

3.5.7 Regulatory Technology and Compliance Analytics

A growing body of work examines how institutions operationalise these obligations through regulatory technology (RegTech). Proposed frameworks address financial transparency and fraud reporting accuracy, data driven compliance analytics, compliance risk in emerging economies, and the cost efficiency of compliance (Bello et al., 2025b; Akomolafe et al., 2025; Akomolafe et al., 2023b; Mensah et al., 2025). Reviews of real-time compliance

pipelines, automated governance in multi-country networks, control effectiveness for technology risk and regulatory reporting, SOX compliance in cross-border auditing, and data driven tax compliance in banks describe how monitoring can be automated (Uchechi et al., 2022a; Uchechi et al., 2025; Okwesa et al., 2023; Agu et al., 2023a; Bola-Sadipe et al., 2022). Blockchain based recordkeeping for audit readiness, collaborative governance for cross-border payment data sharing, blockchain based regulatory transparency, and regulatory adaptation of cross-border payment products (Anichukwueze et al., 2021; Akomolafe et al., 2025a; Kumuyi et al., 2023; Olaogun et al., 2023) show how infrastructure choices affect compliance. Analyses of integrated regulatory risk leadership (Ominyi et al., 2026a) and of the unintended compliance burdens created by financial regulation (Fobellah, 2025c) caution that layering new AI rules on existing regimes can increase cost without improving outcomes unless requirements are coordinated.

Table 4. Comparative overview of key regulatory instruments affecting AI in lending. (as of November 2026)

Jurisdiction	Key instruments	Status in 2026	Approach to bias	Approach to transparency
European Union	AI Act (credit scoring high risk); GDPR; Consumer Credit Directive 2023/2225; EBA loan origination guidelines	High risk AI duties deferred to 2 Dec 2027; CCD applies from 20 Nov 2026	Data governance and bias examination; fundamental rights impact assessment	Right to explanation (GDPR, CJEU case law, CCD, AI Act); human intervention
United States (federal)	ECOA and Regulation B; FCRA; FHA; SR 26-2	Disparate impact removed from Reg B (21 Jul 2026); SR 11-7 replaced (17 Apr 2026)	Disparate treatment and intentional proxy use; disparate impact persists under FHA	Specific, accurate adverse action reasons (CFPB Circulars 2022-03, 2023-03)
United States (states)	State UDAP and fair lending laws; Colorado SB 26-189; AG guidance	Colorado law effective 1 Jan 2027; active AG enforcement (e.g., Massachusetts)	Outcome testing expected in some states	Notice, disclosure, and appeal rights for automated decisions
United Kingdom	FCA Consumer Duty; Equality Act; UK data	Principles based; no AI statute	Fair treatment and outcomes; equality law	Consumer understanding; automated

Jurisdiction	Key instruments	Status in 2026	Approach to bias	Approach to transparency
	protection law			decision safeguards
Nigeria	FCCPC Digital Lending Regulations 2025; Nigeria Data Protection Act 2023	In force since 21 Jul 2025	Limited explicit treatment	Disclosure of terms; data use limits

Sources: compiled from primary instruments and regulatory publications cited in the text.

Table 4 should be read alongside the compliance literature reviewed in Section 3.5.7 and the AI governance literature reviewed in Section 3.6, which together describe how institutions translate divergent legal requirements into common internal controls.

3.6 Conceptual Model

The literature synthesis shows that the risks and benefits of AI in lending are not properties of algorithms alone. They arise from interactions between the data and design choices that feed a model, the decisions the model supports, the mechanisms through which those decisions can harm or help consumers, and the governance and regulatory conditions under which the system operates. To integrate these findings, this section proposes a conceptual model of responsible AI lending (Figure 1). The model is intended as an organising framework for research and practice and as a source of propositions that future empirical work can test.

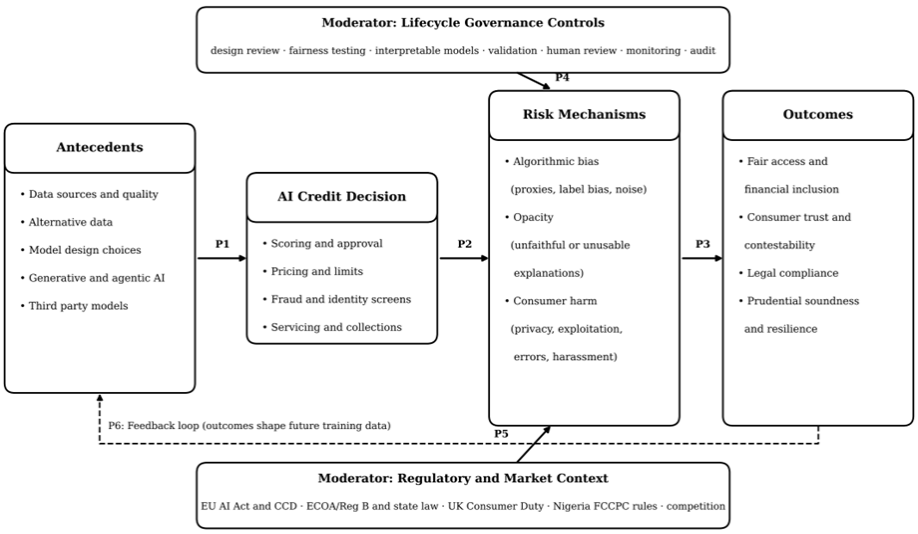

Figure 1. Conceptual model of responsible AI lending: antecedents, decision, risk mechanisms, outcomes, moderators, and feedback. (P1 to P6 denote propositions)

3.6.1 Constructs

Antecedents. The inputs and design choices that shape an AI credit system: the sources and quality of data, including alternative data (Berg et al., 2020; Björkegren & Grissen, 2020); the choice of model class, target variable, and features (Lessmann et al., 2015; Fuster et al., 2022); the use of generative and agentic AI in surrounding workflows (Ajala et al., 2026; Nwakamma et al., 2024b); and reliance on third party models and data (Tonoyan et al., 2024a; Aliliele et al., 2023b).

AI credit decision. The set of automated or AI supported decisions that affect consumers across the lending lifecycle: approval and scoring, pricing and credit limits, fraud and identity screening, and servicing and collections (Okoli et al., 2022b; Fadayomi et al., 2024; Osuji et al., 2021).

Risk mechanisms. Three channels through which AI decisions can produce adverse outcomes. *Algorithmic bias* arises from proxies, label bias, selective labels, and unequal data quality (Blattner & Nelson, 2021; Lakkaraju et al., 2017). *Opacity* arises when explanations are unavailable, unfaithful, unstable, or unusable by consumers (Rudin, 2019; Slack et al., 2020). *Consumer harm* covers privacy intrusion, exploitative pricing, errors without recourse, and abusive collection practices (Hurley & Adebayo, 2016; FCCPC, 2025).

Outcomes. The ends that responsible lending seeks to secure: fair access to credit and financial inclusion, consumer trust and the ability to contest decisions, compliance with law, and the prudential soundness and resilience of lenders (Agboada et al., 2022; Ashore-Onisemo & Unamma, 2022a).

Moderators. Two sets of conditions shape the strength of the relationships above. *Lifecycle governance controls* include design review, fairness testing, interpretable modelling, independent validation, human review, monitoring, and audit (NIST, 2023; Federal Reserve et al., 2026) (Ominyi & Anichukwueze, 2024; Elebe & Anunagba, 2025). *Regulatory and market context* includes the applicable legal regime (such as the EU AI Act and Consumer Credit Directive, ECOA and state law, the UK Consumer Duty, or Nigeria's digital lending rules) and the intensity of market competition.

Feedback. Lending outcomes become future training data. Denials, adverse pricing, and defaults recorded under one model shape the data on which the next model is built, which can entrench or correct earlier patterns.

3.6.2 Propositions

The model yields six propositions, each grounded in the literature synthesis:

1. P1 (Antecedents and decisions). The greater the use of flexible models and high dimensional or alternative data, the greater the predictive accuracy of AI credit decisions, but also the greater the capacity of those decisions to reconstruct protected characteristics through proxies (Fuster et al., 2022; Navya et al., 2026).

2. P2 (Decisions and risk mechanisms). AI credit decisions increase the likelihood of algorithmic bias, opacity, and consumer harm when they rely on noisy or unrepresentative data, complex models explained only post hoc, or data collected without consumers' reasonable expectation (Blattner & Nelson, 2021; Krishna et al., 2022) (Unamma & Ashore-Onisemo, 2023).

3. P3 (Risk mechanisms and outcomes). Algorithmic bias, opacity, and consumer harm each reduce fair access, consumer trust, and legal compliance, and in combination they increase legal, reputational, and prudential risk for lenders (Massachusetts Attorney General, 2025) (Ominyi & Anichukwueze, 2023).

4. P4 (Governance moderation). Lifecycle governance controls weaken the relationship between AI credit decisions and the three risk mechanisms; the effect is strongest when fairness testing and explanation design are built in before deployment rather than added afterwards (Rudin, 2019; Kozodoi et al., 2022) (Unamma et al., 2025b; Ashore-Onisemo et al., 2025).

5. P5 (Regulatory moderation). The regulatory and market context moderates both the incidence of risk mechanisms and their consequences. Regimes that require explanation, human review, and outcome testing (for example the EU from 2026 to 2027) strengthen governance and reduce harm, whereas narrowing of liability theories (for example the 2026 Regulation B amendments) weakens external incentives for outcome testing unless offset by state law, private litigation, or market discipline (CFPB, 2026; CJEU, 2025) (Ominyi et al., 2024b).

6. P6 (Feedback). In the absence of monitoring and correction, adverse outcomes for disadvantaged groups feed back into training data and amplify future disparities; active monitoring, complaint analysis, and periodic retraining with fairness constraints can reverse this dynamic (Unamma et al., 2019b; Okwesa et al., 2026).

3.6.3 Operationalising the Model: Lifecycle Governance Controls

Moderator P4 is operationalised through lifecycle controls. Drawing on the literature and on the common elements of the EU AI Act, US model risk and fair lending expectations, enforcement settlements, and international standards, Table 5 sets out controls for each stage of the model lifecycle. They are designed to be robust to regulatory divergence: an institution that follows them should be positioned to comply with stricter regimes while remaining defensible under more permissive ones.

Table 5. Lifecycle governance controls for responsible AI lending.

Lifecycle stage	Key controls	Bias focus	Transparency and consumer focus
1. Purpose and design	Define use case, target variable, and risk tier; accountable owner; legal review	Assess whether target and population encode historical discrimination	Decide explanation strategy before modelling; prefer interpretable models where feasible
2. Data	Data inventory and lineage; minimisation; quality checks; consent and lawful basis	Screen variables for proxy risk; assess representation of groups	Exclude data consumers would not reasonably expect, or disclose its use
3. Development	Benchmark against simpler models; document choices; monotonic constraints	Fairness testing across groups; search for less discriminatory alternatives	Validate that reason codes are faithful and stable
4. Independent validation	Challenge by a team independent of developers	Validate fairness metrics and proxy analysis	Test explanation accuracy and consumer comprehensibility
5. Deployment	Human oversight for edge cases; controls on overrides	Monitor overrides for differential treatment	Specific adverse action reasons; clear routes to appeal and human review
6. Monitoring	Drift, performance, and stability monitoring; complaint analysis	Periodic outcome disparity reporting	Track disputes, corrections, and appeal outcomes
7. Third parties and generative AI	Vendor due diligence; contractual audit rights; inventory of generative and agentic tools	Require vendor fairness evidence	Prevent generative tools from producing reasons not grounded in the scoring model

Source: author synthesis drawing on NIST (2023), Regulation (EU) 2024/1689, Federal Reserve et al. (2026), and Massachusetts Attorney General (2025).

Three principles underpin these controls. First, **fairness testing should continue even where federal law no longer requires disparate impact analysis**, because state law, the Fair Housing Act, foreign regimes, private litigation, and future policy changes all create exposure, and because such testing is the main way to detect unintentional proxy discrimination that can shade into prohibited disparate treatment. Second, **explanation should be designed in rather than bolted on**: choosing interpretable or constrained models where accuracy costs are small reduces reliance on fragile post hoc methods and simplifies compliance with explanation rights in multiple jurisdictions. Third, **governance should extend to every AI tool that influences credit outcomes or consumer communications**, including generative and agentic systems outside formal model risk guidance and models supplied by vendors.

The framework is consistent with a broader literature on AI and risk governance. Conceptual models propose responsible AI governance structures for automated decision systems in regulated industries, enterprise AI governance functions as institutional standards for auditable risk management, a three pillar model linking ethics, data, and workforce readiness, and the integration of legal, financial, and data governance in enterprise AI (Ominyi & Anichukwueze, 2024; Ominyi et al., 2026b; Unamma et al., 2025b; Ashore-Onisemo et al., 2024). The business analyst has been described as an AI transformation broker who aligns stakeholders around responsible automation (Alieme et al., 2025), and human in the loop systems are presented as a structural safeguard (Ashore-Onisemo et al., 2025). On the risk side, frameworks for risk based internal control in banking and insurance, financial resilience through integrated governance and compliance, risk based auditing, operational resilience, and data analytics for audit quality (Akomolafe & Agu, 2019a; Akomolafe & Agu, 2019c; Akomolafe et al., 2023a; Ashore-Onisemo & Unamma, 2022a; Ozowara et al., 2025) provide the institutional scaffolding into which AI controls can be placed.

Monitoring and oversight also benefit from advances in management information. Real-time governance dashboards, executive financial dashboards, data driven executive decision systems, capital allocation analytics, and predictive financial forecasting models (Ashore-Onisemo et al., 2026; Walawalkar et al., 2025; Lawal & Oduleye, 2019b; Lawal & Oduleye, 2021a; Medon & Oduleye, 2024) support board level visibility of model performance and outcomes. Integrated data management for forecasting accuracy, reporting accuracy in

complex audit environments, financial governance in SMEs and nonprofits, strategic accounting for transparency, and comprehensive financial reporting models (Agu et al., 2023b; Kinyanjui et al., 2024; Eboh et al., 2025; Bola-Sadipe et al., 2019; Medon & Oduleye, 2022), together with governance models for transparency and accountability in complex enterprises, FinTech enabled cost transparency, and predictive analytics for regulatory reporting and portfolio oversight in banking (Akhigbe et al., 2025; Odeyemi & Idowu, 2025; Okwesa et al., 2026), illustrate how outcome and fairness metrics can be reported with the same discipline as financial metrics.

3.7 DISCUSSION

The synthesis and conceptual model highlight five issues that cut across the individual literatures.

3.7.1 Accuracy and Fairness Are Not a Simple Trade-off

Much early debate framed responsible AI lending as a trade-off between accuracy and fairness. The evidence reviewed here supports a more nuanced view. Flexible models can be more accurate overall while worsening outcomes for some groups (Fuster et al., 2022), yet many fairness interventions cost little in profit (Kozodoi et al., 2022), and the multiplicity of near equivalent models means that less discriminatory alternatives often exist at negligible accuracy cost. At the same time, part of the observed disparity arises from data quality rather than model choice (Blattner & Nelson, 2021), so no modelling technique can fully resolve it. The relevant question is therefore not whether to trade accuracy for fairness, but which disparities are justified by genuine risk, which are artefacts of data and design, and who bears the cost of reducing them (Bono et al., 2021). Applied audits that show accurate forecasts can still be inequitable (Komi, 2023; Unamma & Ashore-Onisemo, 2023) reinforce this point.

3.7.2 Explanation Is an Accountability Mechanism, Not Only a Disclosure

Legal regimes increasingly treat explanation as a means to an end: enabling consumers to understand, contest, and correct decisions (CJEU, 2025; CFPB, 2023). This has two consequences. First, technically sophisticated post hoc explanations are insufficient if they are unfaithful, unstable, or incomprehensible to consumers (Slack et al., 2020; Krishna et al., 2022). Second, explanation is only meaningful when connected to processes for human review, correction, and redress (Ashore-Onisemo et al., 2025; Unamma et al., 2019b). The literature on audit and assurance (Fobellah, 2025b; Aliliele et al., 2025a) suggests that explanations should also serve internal accountability, enabling validators and auditors to challenge model logic. The strongest position, consistent with Rudin (2019), is to prefer

interpretable models where performance allows, so that the explanation given is the model itself.

3.7.3 The Inclusion Promise Depends on Context

Alternative data and AI can extend credit to borrowers excluded by traditional scoring (Di Maggio et al., 2022), and the emerging market literature describes digital lending as a driver of SME growth and financial inclusion (Okafor et al., 2021; Agboada et al., 2022). Yet the same technologies have enabled intrusive data collection, high cost short term loans, and abusive collection practices, prompting regulatory intervention such as Nigeria's 2025 regulations (FCCPC, 2025). The conceptual model explains this duality: the antecedents that enable inclusion (new data, new models) are also those that intensify the risk mechanisms, and the net effect depends on governance and regulatory moderation. Inclusion claims should therefore be judged on measured outcomes for borrowers, including repayment burden and wellbeing, not on approval rates alone.

3.7.4 Regulatory Divergence and Convergence on Controls

The 2026 regulatory landscape shows clear divergence in legal theories: the EU strengthened explanation rights while deferring high risk AI duties, the United States removed disparate impact from Regulation B and replaced its model risk guidance, Colorado narrowed its AI law, and Nigeria focused on conduct and data. Beneath this divergence, however, the control expectations are converging. Documentation, validation, accurate adverse action reasons, human review, monitoring, and third party oversight appear in almost every regime and in voluntary standards (NIST, 2023). Compliance literature emphasising integrated, automated compliance pipelines (Uchechi et al., 2022a; Akomolafe et al., 2025) suggests that institutions will increasingly manage divergence by adopting a common internal standard set at the level of the strictest major market, and then documenting jurisdiction specific variations.

3.7.5 The Generative AI Governance Gap

The most significant emerging gap concerns generative and agentic AI. These systems increasingly shape the data entering credit models and the communications consumers receive, but US model risk guidance expressly excludes them (Federal Reserve et al., 2026), and the empirical literature on their use in lending is thin. Technical research on hallucination, evaluation, and agent security (Ajala et al., 2026; Nwakamma et al., 2024a; Nwakamma et al., 2024b) provides building blocks, but there is not yet an accepted standard for validating a language model that drafts adverse action reasons or extracts income from documents. Until such standards emerge, the conceptual model implies that institutions

should treat these tools as part of the credit decision system and extend lifecycle governance to them.

3.8 Implications

3.8.1 Implications for Lenders and Practitioners

- **Maintain outcome based fairness testing** even where federal law no longer requires disparate impact analysis, because state law, the Fair Housing Act, foreign regimes, and future policy changes all create exposure, and because testing is the main way to detect proxy discrimination (Unamma & Ashore-Onisemo, 2023; Ominyi & Anichukwueze, 2023).
- **Design for explanation from the start** by preferring interpretable or constrained models where accuracy costs are small, and by validating that adverse action reasons are faithful, stable, and understandable (CFPB, 2023; Rudin, 2019).
- **Inventory every AI tool that touches credit outcomes or consumer communications**, including generative and agentic tools, fraud screens, and vendor models, and apply proportionate lifecycle controls to each (Tonoyan et al., 2024a; Nwakamma et al., 2024b).
- **Prepare for human review and appeal rights** under the EU Consumer Credit Directive from November 2026 and Colorado's law from January 2027, by building review workflows, record retention, and complaint analysis into operations (Unamma et al., 2019b; Ashore-Onisemo et al., 2025).
- **Minimise data** and avoid sources that consumers would not reasonably expect, particularly in mobile lending, where intrusive data access has been a major source of harm (FCCPC, 2025) (Ominyi & Anichukwueze, 2022a; Oyesiji et al., 2026).

3.8.2 Implications for Regulators and Policymakers

- **Clarify expectations for generative and agentic AI** in lending, which currently fall outside US model risk guidance and lack sector specific standards elsewhere.
- **Coordinate requirements across regimes** to reduce the compliance burden of overlapping AI, data protection, consumer credit, and anti-discrimination rules, focusing on shared controls such as documentation, validation, explanation, and human review.
- **Strengthen the evidence base** by collecting and publishing outcome data on AI lending, including approval, pricing, and complaint patterns by group, while respecting privacy (Okwesa et al., 2026).
- **In emerging markets, pair conduct and data rules with model governance** so that digital lending regulation addresses fairness and explanation as well as harassment and data abuse (Fadero et al., 2021; Ominyi & Anichukwueze, 2022a).

3.8.3 Implications for Consumers and Civil Society

Consumers increasingly have rights to explanations, human review, and correction of data, particularly in the EU and in some US states. Consumer organisations, ombudsmen, and civil society can help translate these rights into practice by educating borrowers, aggregating complaints, and testing whether explanations and review processes work. Complaint data, in particular, are a valuable signal of systematic model errors (Adeyelu, 2018; Unamma et al., 2019b).

3.8.4 Theoretical Implications

The review contributes to theory in three ways. First, it integrates technical, legal, and consumer protection literatures that are usually studied separately into a single conceptual model with explicit mediating mechanisms and moderators. Second, by including a feedback loop, it treats AI lending as a dynamic system rather than a one-off prediction problem, consistent with work on selective labels and performative effects (Lakkaraju et al., 2017). Third, by drawing on a large emerging market critical review corpus alongside the international literature, it shows that the relative importance of the three risk mechanisms varies by context, with consumer harm through data abuse and collection conduct more salient in some emerging markets and algorithmic bias more salient in mature credit markets.

4. CONCLUSION

4.1 Concluding Remarks

AI has become integral to credit risk assessment, and its use will continue to deepen with the spread of alternative data and generative AI. The evidence reviewed here shows that AI can improve predictive accuracy and extend credit to underserved borrowers, but that these benefits are neither automatic nor evenly distributed. Flexible models can reconstruct protected characteristics from proxies, data quality differences can produce disparities that better algorithms alone cannot fix, and post hoc explanations can be inaccurate, unstable, or manipulable. Consumer protection concerns extend beyond fairness to privacy, contestability, exploitative pricing, abusive digital lending practices, and third party dependence.

The regulatory picture in 2026 is one of divergence. The European Union has kept credit scoring within a high risk AI regime while delaying its application, and has strengthened explanation and human review rights through case law and the revised Consumer Credit Directive. The United States has narrowed federal fair lending theory and modernised model risk guidance while leaving generative AI outside it, as states pursue their own and

sometimes unstable paths. Emerging markets such as Nigeria are prioritising conduct and data protection in digital lending.

In this environment, responsible lending cannot depend on the minimum requirements of any single jurisdiction. Lenders that embed fairness testing, faithful explanation, meaningful human review, and lifecycle governance into their AI systems will be better placed to serve consumers, withstand legal and reputational scrutiny, and adapt to future regulatory change. For researchers and policymakers, the priority is to move from static benchmark studies to causal, consumer centred, and context specific evidence on how AI is actually reshaping access to credit.

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