American International Journal of Business Management (AIJBM)
ISSN- 2379-106X, www.aijbm.com Volume 9, Issue 06 (June - 2026), PP 44-53

AI-Driven Credit Risk Assessment in Fintech Lending: Implications for Financial Inclusion, Systemic Risk, and Regulatory Governance

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ABSTRACT: Artificial intelligence (AI) and machine learning (ML) in fintech lending have revolutionized credit risk assessment, enhanced financial inclusion, but raised challenges to governance, such as algorithmic fairness, systemic stability, and regulatory sufficiency. The given paper provides a systematic literature review and analytical synthesis of AI-based credit risk assessment in the context of fintech lending, relying on 30 peer-reviewed articles that were published in 2012 and 2025. The paper compares the performance of ML models to traditional scoring principles, examines the dynamic of financial inclusion and digital exclusion, and suggests a five-stage governance framework called the Integrated AI Credit Risk Framework (IACRF), which is an original operationalization of the SAFE AI principles of statistical accuracy, algorithmic fairness, financial stability, and ethical governance. Results show that ensemble and hybrid explainable AI models have better classification compared to those without governance, and their use without good governance increases inequality, systemic risk, and exceeds regulatory capacity. The paper ends by giving specific policy suggestions to regulators, fintech companies, and multilateral development agencies to find a balance between credit innovation and financial stability as well as borrower equity.

KEYWORDS - Artificial Intelligence in Finance; Credit Risk Assessment; Fintech Lending; Machine Learning Credit Scoring; Financial Inclusion; Algorithmic Bias; Systemic Risk; Explainable AI (XAI)

I. INTRODUCTION

In its contemporary history, the financial services sector is witnessing one of the most significant transformations due to the interplay of big data analytics, artificial intelligence (AI), and the digital platform economics. In this transformation, credit risk assessment has become not just the main place of AI implementation and where the technology has most of its most promising and dangerous implications are felt, but also the location where the technology has had the biggest impacts. Over the decades, the credit risk assessment market has been dominated by more classical statistical models - mainly logistic regression and FICO scoring system, basing their analysis on structured credit bureau information, including payment history, credit usage, and debt-to-income ratios. Although these instruments could offer practical estimates of default probability, they have avoided much of the population with no record of formal credit using bureau coverage at a rate that can be below 20 percent of the adult population, which is especially true in emerging economies where bureau coverage rates can drop to below 20 percent of the adult population [1].

It is against this backdrop that fintech lenders have used AI and ML architectures to process alternative data sources both in scale and speed more than ever before. Mobile phone usage and utility payment history, e-commerce history, and behavioral indicators are some of the proxies of creditworthiness that have been pioneered by platforms like Lending Club, Ant Financial, and PayPal credit and deliver quantifiable financial inclusion benefits [2, 3]. Simultaneously, as opaque, data-dense AI models start proliferating, they have brought about governance issues, which industry standards and regulatory frameworks have not so far addressed.

There are three key tensions of the modern problem of AI-based credit risk assessment. The former is the accuracy explainability trade-off: the new generation of ensemble and deep learning models is more accurate than the traditional scorecards, but are black-box models that are difficult to interpret because of the demands of regulators and borrowers [4, 5]. The second one is the inclusion-bias paradox: alternative data pipelines that credit populations that it previously did not credit are also at risk of incurring structural discrimination and amplifying the effect on the classes being protected, which can lead to disparate effects [6]. The third one is the stability-innovation dilemma: the systemic risk vectors (model herding, procyclicality, and platform contagion) of the interconnectedness of fintech lending platforms cannot be identified or addressed by conventional prudential frameworks [7, 8].

The paper has managed to focus on these tensions based on a systematic review and analysis of the empirical and theoretical literature on AI-based fintech credit risk. It suggests an innovative five-step governance framework, the Integrated AI Credit Risk Framework (IACRF), operationalizing the SAFE AI

principles throughout the entire operational lifecycle of a fintech credit system, and coming up with policy proposals to regulators, practitioners, and development finance institutions. The paper has the following structure: in Section II, the literature review will be done on eight thematic domains; Section III will construct the theoretical framework and IACRF; Section IV will outline the methodology; Section V will summarize the results and discussion, and finally, Section VI will be a conclusion.

II. LITERATURE REVIEW

2.1 Evolution of Credit Risk Assessment: From Traditional Models to AI

Formal credit risk assessment dates back to the logistic regression-based scorecards created in the 1950s and 1960s, with Altman's (1968) Z-score for corporate bankruptcy prediction, and extends through the institutionalization of the FICO score in consumer lending in 1989. The traditional methods presuppose linear relationships between predictors, are vulnerable to multicollinearity, and rely on pre-determined choice of variables - features that are not well aligned to the high-dimensional and nonlinear data conditions of the contemporary digital lending [4, 9]. The shortcomings of bureau-based scoring opened the door to ML methods that can handle complex feature interactions, adapt to new data patterns, and handle unstructured inputs. Since the mid-2010s, decision trees, random forests, gradient boosting machines, especially XGBoost and LightGBM, and neural network architectures have started to enter fintech lending businesses, with improvements of 5 to 15 percentage points over logistic regression models in terms of AUC-ROC [10, 4]. The latest frontier is adding explainability mechanisms, such as SHAP values, LIME, and integrated gradients, to high-performing ML architectures, which partially closes the divide between the performance of a model and regulatory interpretability [5, 11].

2.2 Fintech Lending: Market Structure, Growth Dynamics, and Bank Interactions

The world fintech lending sector has evolved to become a multi-trillion-dollar business, including peer-to-peer (P2P) lending, marketplace lending, balance sheet schemes, embedded finance, and buy-now-pay-later (BNPL). [2] chronicle the way varying fintech business models take advantage of AI to lower underwriting expenses, speed up the process of credit decisioning (from days to seconds), and serve underserved borrower groups not served by existing banks. [12] discovers that fintech lending does not replace access to bank credit in U.S. consumer markets, whereas [13] reveal that the banking market concentration determines the chances of fintech entering the market. According to [1], financial inclusion and development are some of the determinants of fintech and BigTech lending volumes that are recorded. Notably, [14] discovered that the fintech credit-exposed firms show higher bankruptcy rates in troughs, which casts doubt on the idea that AI-enhanced credit expansion can lead to a faster misallocation of risk in some segments of the credit portfolio and highlights the necessity to incorporate the through-the-cycle performance of credit models, as opposed to in-sample accuracy.

2.3 Machine Learning Models for Credit Risk: Comparative Performance

This systematic review by [4] confirms that the ensemble techniques have always achieved higher performance than the logistic regression benchmarks on all the datasets, evaluation metrics, and markets. The use of gradient boosting algorithms, especially XGBoost and LightGBM, has become the tool of choice in fintech credit scoring, providing better missing data behavior, resistance to overfitting, and good tabular data behavior. [10] illustrate that a hybrid XAI model that takes the form of gradient boosting with SHAP-based explainability can attain an AUC-ROC of 0.89 as compared to a logistic regression baseline of 0.76, and meets the adverse action notice criteria. Similar conclusions are made by [11] with regard to trade credit risk, and [9] demonstrate that LSTM networks give an AUC-ROC over 0.90 with enterprise credit data used, but at a high interpretability cost. The results show that there is a performance hierarchy: deep learning models have marginal benefits in data-rich settings, and ensemble approaches are the most risk-adjusted option in real-world fintech applications. Table 1 summarises comparative performance evidence in the literature reviewed.

Table 1: **Comparative performance of ai/ml models in credit risk assessment**

Model Type	AUC-ROC Range	Gini Coeff.	Interpretability	Fairness Compliance	Regulatory Suitability
Logistic Regression	0.68 – 0.77	0.36 – 0.54	High	Partial	High
Decision Tree	0.70 – 0.78	0.40 – 0.56	High	Partial	High
Random Forest	0.79 – 0.86	0.58 – 0.72	Low-Medium	Partial	Medium
XGBoost / LightGBM	0.83 – 0.91	0.66 – 0.82	Low	Partial	Medium
LSTM / Deep Learning	0.85 – 0.93	0.70 – 0.86	Very Low	Unclear	Low

Hybrid XAI (SHAP/LIME)	0.84 – 0.92	0.68 – 0.84	Medium-High	Yes (Conditional)	Medium-High

2.4 Financial Inclusion and AI-Driven Credit Expansion

[3] shows that when used on alternative data (mobile usage, records of digital payments, behavioral indicators), ML models produce creditworthiness estimates of thin-file borrowers just as accurate as the traditional scoring on bureau-rich groups, and it is especially interesting in Sub-Saharan Africa, South Asia, and Southeast Asia. [14] list digital financial literacy and perceived regulatory support as the most important mediating variables, and it is important to highlight that the groups facing the highest likelihood of benefiting due to AI-driven credit expansion are the same most vulnerable to using AI-based credit products. In a study by [16], the benefits of fintech inclusion are being recorded to be among digitally connected groups, posing a second-order challenge of exclusion. [17] also adds that the pace of digital credit and its magnitude pose the risk of overleverage in newly added borrowers within a short time. The composite financial inclusion index of developing economies presented in the study by [18] shows that access indicators tend to conceal quality differences. Nominally included populations can have AI-generated credit products that have prohibitive interest rates and punitive default fees that harm and do not improve financial well-being.

2.5 Algorithmic Bias, Fairness, and Ethical Dimensions

Algorithms' bias in credit scoring. The systematic bias of AI models to hurt the interests of the protected groups is known as algorithmic bias: racial minorities, women, and older adults. [6] show that behavioral biases are coded in an ordered manner in AI systems that are trained on biased data in the past. IJCATR (2025) analysis reveals that the discriminatory patterns are seen with the use of XAI techniques, whereas visibility is not necessarily followed by remediation. The sources of bias can be categorized into three pipeline stages: pre-processing (historical training data based on past discrimination), in-processing (model architecture decisions implicitly related to the protected attributes), and post-processing (use on populations that are not in the same distribution as the training). [5] posit that technical debiasing, such as re-sampling, adversarial debiasing, and fairness constraints, cannot be effectively used without institutional accountability mechanisms, such as having mandatory audits on algorithms, publishing fairness measurements, and allowing recourse rights. The lack of these in the majority of the regulatory frameworks is the key gap in governance in the area of algorithmic fairness.

2.6 Systemic Risk, Financial Stability, and Fintech Interconnectedness

[7] prove the existence of tail-risk spillovers between financial institutions, and that correlated asset exposures increase the tail-risk spillovers between financial institutions, a phenomenon that AI lending promotes in the lending system via model convergence. In their record, [8] report a high level of systemic risk, which is due to the high growth rate of credit, the low capital adequacy, and reliance on wholesale funds. [19] lists three channels of systemic risk: the concentration of powerful platforms, interconnectedness via API integrations with banking counterparties, and the lack of accessibility to the algorithms behind credit decisions made by algorithms by supervisors. [20] determine that systemic risk propagation in bank-firm networks is greatly moderated by the regulatory policy environment, whereas [21] build on this to compound systemic risk due to the interdependence of finance, technology, energy, and geopolitical systems - environments that AI credit systems can enhance procyclical allocation.

2.7 Regulatory Frameworks and AI Governance in Lending

[22] presents the initial examination of the problem of AI governance in financial services, which he describes as regulatory arbitrage, systemic openness, and discriminatory results as the three main risks that the government needs to approach in its strategy. [23] defines credit scoring AI as a high-risk category, which must have conformity tests, documentation of training data, human supervision, and explainability compliance. The Basel Committee has provided guidance on model risk management that requires validation of AI credit models, monitoring, and documentation of AI credit models. The U.S. CFPB has applied the requirements of the Equal Credit Opportunity Act to AI-generated decisions relating to adverse actions, but has not applied the requirements to non-bank fintech platforms whose enforcement ability is limited. A structural issue that is identified in the bibliometric analysis of [24] is regulatory arbitrage, i.e., the migration of model deployment to a jurisdiction with lighter regulation for fintech firms that needs to be coordinated internationally by the Financial Stability Board and Basel Committee.

2.8 Identified Gaps in the Existing Literature

The contributions to this paper are inspired by four gaps. First, the streams of research on the model performance, inclusion, bias, and systemic risk are relatively isolated, and there are very few studies that combine model-level analysis and macro-prudential assessment. Second, the literature on AI credit dynamics is strongly biased towards North American and European situations, and little is known about the AI credit dynamics in Sub-Saharan African and Southeast Asian fintech markets. Third, there is no currently existing

system of governance that considers model-level explainability, fairness of borrowers, and systemic stability of the market at the same time in a single architecture that is tuned to fintech. Fourth, full-cycle empirical studies of the performance of AI credit models do not exist to allow sufficient evaluation of the procyclicality risks.

III. THEORETICAL FRAMEWORK

3.1 Theoretical Anchors

The article is based on three theoretical traditions that are complementary. The information asymmetry theory [25, 26] provides that credit market inefficiencies are a result of the inability of lenders to completely monitor the type of borrower. Thought to be advanced information processors, AI credit systems are theorized to decrease the lender-side asymmetries with increased and more diverse datasets. But they also introduce new borrower-side asymmetries, hidden algorithmic judgments, which could not be comprehended, challenged, or acted upon by those impacted, creating a lack of fairness and accountability, which the SAFE AI literature recognizes [5]. The literature on financial innovation [27] sees AI-driven fintech as an institutional change that can be caused by the interplay of the availability of data, the power of computers, and the opportunity of regulation all of which are essentially institutional, but not technical, in nature. The macro-prudential theory behind the development of the correlated AI credit models is known as systemic risk theory [7], which is based on the tail-risk spillover effects of generating systemic vulnerability due to the existence of monoculture risks that are not diversifiable.

3.2 The SAFE AI Framework

The IACRF normative architecture is based on the normative architecture of [5] SAFE AI framework. The four SAFE pillars, Statistical accuracy, Algorithmic fairness, Financial stability and Ethical governance are operationalized in the context of fintech lending as: (a) minimum, validated out-of-sample performance thresholds; (b) published parity conditions across the three or more protected groups with audited disparate impact; (c) stress-tested resistance to procyclical behavior, model herding and systemic The SAFE framework is claimed to be more suitable in the high-stakes credit situations than single-objective accuracy optimization since it is a framework that takes into account all the aspects of the governance risk simultaneously.

3.3 The Integrated AI Credit Risk Framework (IACRF)

The main theoretical contribution of the paper is the IACRF: a multi-level governance framework that is a map of four pillars of the SAFE AI onto the operational lifecycle of a fintech credit system in five consecutive, iterative steps. The framework is developed in a way that it is applicable to both mature and emerging markets, where the regulation is at either the firm or regulatory interface level. The IACRF architecture is shown in Fig.1

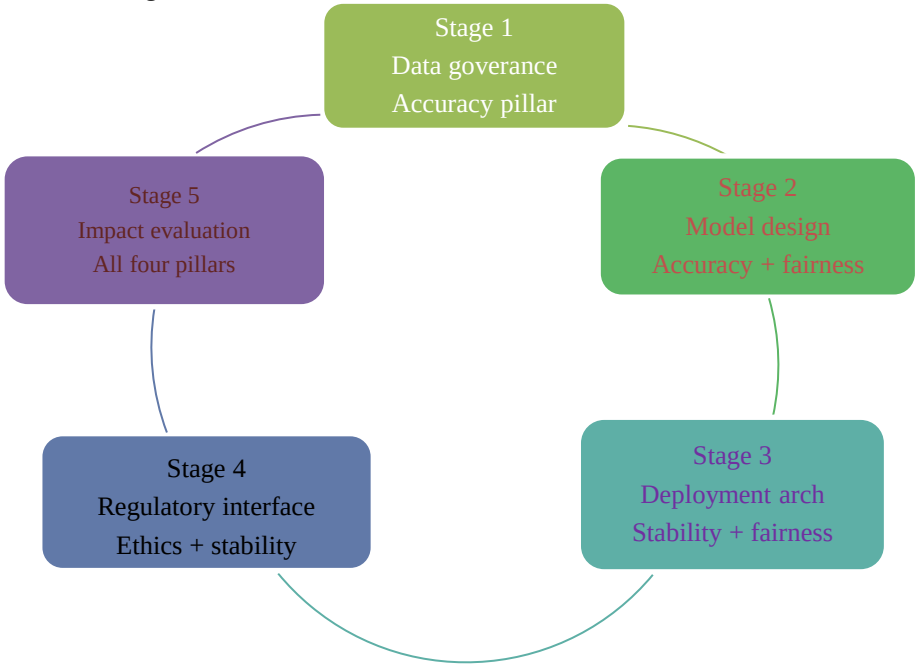

Figure 1: The integrated ai credit risk framework (iacrf) — conceptual architecture

Stage 1: Data Governance: The area deals with the data sourcing, quality management, consent architecture, training data bias audit, and representativeness standards, and operationalizes the SAFE accuracy pillar. Stage 2: Model Design regulates the choice of architecture, integration of fairness constraints, the

specification of explainability mechanisms, a documentation of proxy variables, as well as pre-deployment bias audits, operationalising SAFE accuracy and fairness. Stage 3: Deployment Architecture takes care of real-time scoring infrastructure, performance degradation checks, distributional shift checks, human override checks, regulatory audit trail maintenance, and operationalizes SAFE stability and fairness. Stage 4: Regulatory Interface regulates model validation documentation, adverse action notice procedures, supervisory coordination, and periodic model risk assessment, operationalises SAFE ethics and stability. Stage 5: Impact Evaluation includes financial inclusion impact analysis by demographic groups, systemic risk monitoring, the presence of market-level credit correlation and concentration, and public impact reporting, and puts all four SAFE pillars into action at once.

3.4 Theoretical Propositions

The IACRF and literature synthesis give rise to four propositions: (P1) AI credit models are more predictive than traditional methods but have interpretability limitations leading to a conflict of regulation in adverse-action jurisdictions. (P2) Fintech lending based on AI financial inclusion benefits in data-rich settings, but does not reach the digitally low populations, enabling a second-order dynamic of AI-based exclusion. (P3) The systemic risk is exacerbated by market-wide adoption of correlated AI credit models that create tail-risk spillovers, and the model herding and coordinated credit tightening of models, which have larger tail-risk spillovers than traditional credit monocultures. (P4) Adoption of IACRF-specified governance mechanisms, such as explainability integration, bias auditing, and systemic risk monitoring, is positively linked to regulatory compliance and financial stability in AI-driven lending.

IV. METHODOLOGY

4.1 Research Design and Protocol

The present paper has a position of interpretivist-constructivist in a qualitative research design, which is theory-building in nature. It combines both published empirical and theoretical studies to formulate the IACRF and come up with policy implications, as is customary in high-impact journals in finance to contribute to a theoretical framework [2, 24]. The review of the literature is based on a PRISMA-inspired guideline. Searches were done and regulatory repositories of the European Banking Authority, the U.S CFPB, and the Financial Stability Board. Keywords were: 'AI credit risk,' machine learning fintech lending, algorithmic credit scoring, and fintech systemic risk. Secondary terms were: explainable AI finance, algorithmic bias credit, financial inclusion fintech, and credit model governance. This was during the period 2012-2025, but with a focus on 2021 and beyond. Preliminary search results of about 280 documents were narrowed down by filters such as duplicates, title and abstract filtering, and quality filtering that filtered out non-peer-reviewed sources to get a final corpus of 30 peer-reviewed articles and regulatory reports. Fig. 2 shows how the screening is done. The analysis and framework development of comparative models will be conducted at this phase.

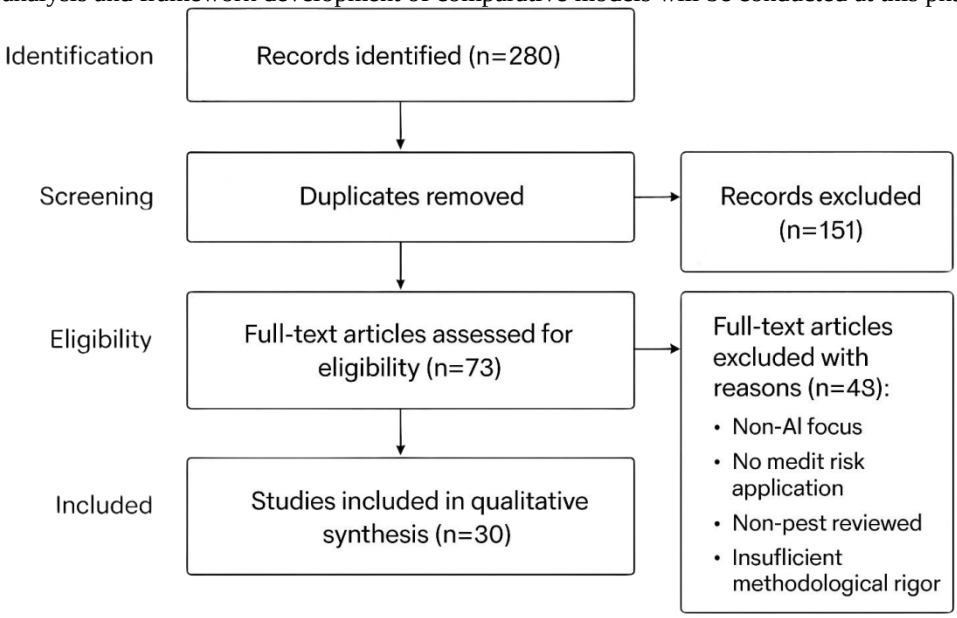

Figure 2: Prisma informed literature search and screening flowchart

4.2 Comparative Model Analysis and Framework Development

To analyze the performance of the comparative model in Section V, performance information reported in studies reviewed is gathered and tabulated into a comparative table. Measurements AUC-ROC, Gini

coefficient, and KS statistic are tabulated by model type with performance ranges instead of point estimates being used to address heterogeneity in cross-study characteristics of the datasets and their methodology. The IACRF is formulated using the iterative framework construction approach of [28]. Theory and evidence are used to construct the theory using theory as the building blocks, and then iterate the relationship among the building blocks to develop sufficient specifications in the framework to create testable propositions. The framework constructs are checked against published frameworks of fintech governance by a consistency check to make sure the structures are complete.

V. RESULTS AND DISCUSSION

5.1 AI Model Performance: Comparative Analysis

The evidence of the comparison proves Proposition 1. Gradient boosting models are able to attain values of 0.83-0.91 in AUC-ROC, which are 7-19 percentage points higher than the logistic regression baselines [4, 10]. Such returns have an economic impact: a 5-percentage-point improvement in the AUC-ROC is directly translated into lower levels of false positives (creditworthy borrowers denied credit) and false negatives (defaulters granted credit) rates, which improve the quality of the portfolio and access to credit by borrowers. The best balance between performance and explainability is the hybrid XAI model [10]: SHAP attribution in a gradient boosting framework can be applied to achieve almost the same accuracy of the ensemble as well as meet the adverse action criteria. Nonetheless, SHAP explanations are local models, which might not capture the behavior of global models, and their implementation is too complex to be adopted by smaller fintech operators. The highest reported performance (AUC-ROC > 0.90) comes with LSTM architecture, which is virtually incompatible with EU AI Act high-risk classification requirements on its black-box nature and therefore, is prone to be adopted by the less-regulated market-driven force of emerging markets, a regulatory arbitrage dynamic that needs supervisor consideration [9].

5.2 Financial Inclusion: Opportunities and Structural Contradictions

Evidence reveals that there is qualitative support for Proposition 2. In new market environments, AI credit models on alternative data increase the rate of approval of thin-file and unbanked borrowers by 20 to 40 percentage points [3], which is an appreciable gain in terms of access to credit to small business owners, gig economy workers, and rural households, who relied on informal credit before. There are limits to inclusionary potential, however, due to structural contradictions. The invisibility of some groups of people that do not have access to smartphones, connectivity, or a history of digital transactions leads to a coverage gap that AI models fail to predict unless non-digital sources of data are included [16]. Although allowing the approval of excluded borrowers potentially places them in high-risk pricing tiers that would earn high interest rates, potentially far exceeding market rates, AI risk stratification granularity can also be dynamic in that nominal inclusion comes at a cost that can lead to financial ill health [17, 15]. Table 2 provides an overview of financial inclusion indicators in an AI-driven lending setting, by region.

Table 2: **Financial inclusion metrics across ai-driven lending contexts by region**

Region	Platform Type	Key Alternative Data	Approval Rate Uplift	Interest Rate Premium	Digital Exclusion Risk
Sub-Saharan Africa	Mobile Money / P2P	Mobile usage, M-PESA, airtime	30–45%	8–18% above base	Very High
Southeast Asia	Digital Bank / BNPL	E-commerce, ride-share, social	20–35%	5–14% above base	High
Latin America	Marketplace Lending	Bill payment, utility, telco	15–28%	4–12% above base	Medium-High
European Union	Embedded Finance / BNPL	Open banking, PSD2 data	8–15%	1–5% above base	Low-Medium
North America	Fintech Marketplace	Rent, utility, gig income	10–20%	2–8% above base	Low

5.3 Algorithmic Bias: Technical Evidence and Institutional Imperatives

The argument that institutional accountability structures, in conjunction with technical debiasing, are necessary is strongly supported by the evidence [5]. [6] show that AI systems can produce behavioral biases methodically encoded within their designs based on the biases in the historical data used to train them - a credit model that learns the discriminatory approval and default patterns of decades learns to recapitulate those biases as predictions, despite not being trained to do so on purpose. The XAI analysis of the IJCATR (2025) establishes that SHAP and LIME are more effective than naive debiasing in identifying the existence of discriminatory patterns. Still, it is not able to remediate them, and that performance-fairness trade-offs render naive debiasing commercially unfeasible among thin-margin fintech operators. The key institutional loophole is that in most major regulatory frameworks, such as the [23], mandatory independent bias auditing, disclosure of public fairness metrics, and enforceability of a right to recourse by borrowers are not mandatory, including the [23], which provides conformity assessment documentation, but does not mandate periodic third-party audits or disclosure of fairness metrics to the public. The priority regulatory reform to bridge this gap would be to set up mandatory bias auditing requirements and to enforce this requirement by the supervisory authority.

5.4 Systemic Risk Propagation Pathways

Systemic vulnerability is enhanced by three different propagation pathways, which amplify the effects of AI-based fintech lending and support Proposition 3. Model herding is caused by converging industry-wide to similar gradient boosting architectures, and overlapping alternative data pipelines: a macroeconomic shock that causes the predictive value of behavioral data to fall at once causes credit assessments of all institutions using that information to become coordinated in tightening their credit policies, a phenomenon that is directly analogous to the correlated asset exposure problem reported by [7]. The AI models trained on expansionary data can be procyclical because they can implicitly link good times with creditworthiness and can produce permissive calibrations when there is a boom and sudden contractions when there is a downturn, and amplify the business cycle via the credit channel [21]. Contagion between platforms occurs as a result of institutional interconnectedness, which comes in the form of API integrations, similar banking infrastructure, and secondary market securitization: a model failure in governance or a cyberattack on a large platform at machine speed spreads to investors, counterparty banks, and secondary market participants even before the conventional risk systems can react [8].

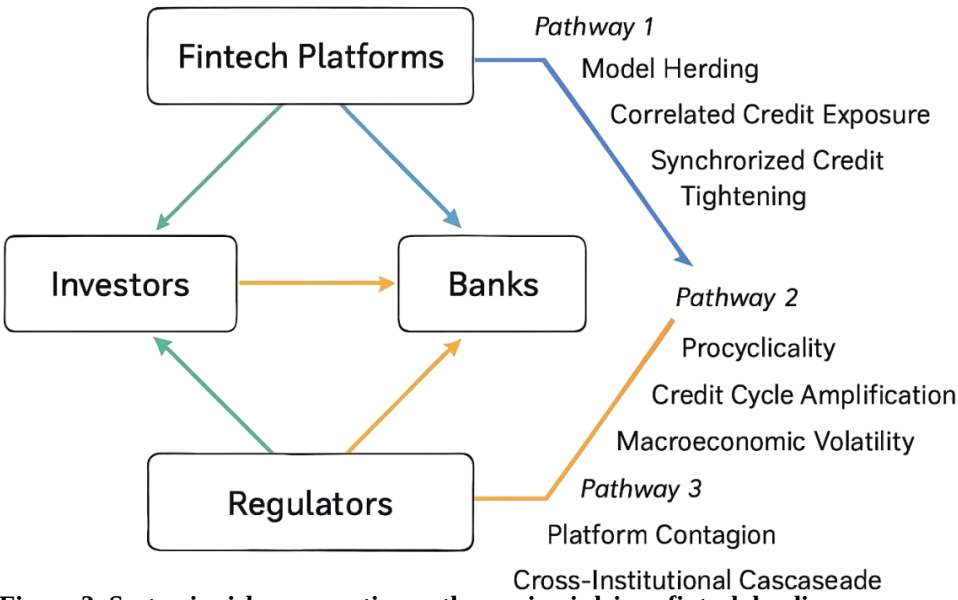

Figure 3: **Systemic risk propagation pathways in ai-driven fintech lending**

5.5 Regulatory Governance: Comparative Jurisdictional Analysis

The comparative study proves the existence of a disjointed and jurisdiction-based unequal governance environment. Table 3 looks at the AI credit governance frameworks in five regulatory jurisdictions in aspects that are directly pertinent to the SAFE AI pillars.

Table 3: **Comparative ai credit governance frameworks by jurisdiction**

Jurisdiction	Primary Instrument	Explainability Req.	Bias Audit Mandate	Model Validation Std.	Enforcement	Gov. Gap Score
United States	ECOA / CFPB Guidance	Partial (Adverse Action)	No (Voluntary)	SR 11-7 (Banks only)	CFPB Civil Action	3 / 5
European Union	EU AI Act (2024)	Yes (High-Risk Class)	Yes (Conformity Assess.)	CE Marking + EBA	EBA / Nat. Supervisors	2 / 5
United Kingdom	FCA Consumer Duty	Yes (Outcome-Based)	Yes (Fair Treatment)	FCA Model Risk Guidance	FCA Supervisory	2 / 5
China	PBOC Algorithm Reg.	Partial (Disclosure)	Partial	PBOC Tech. Standards	PBOC Administrative	3 / 5
Emerging Markets	Varies / Minimal	Rarely Required	Rarely Required	Absent or Informal	Limited Capacity	5 / 5

There are two overall findings. To start with, the [23] is the most up-to-date best-practice model (closest to Stage 4 (Regulatory Interface) of the IACRF), but it is still not sufficient in the systemic risk aspect (there is no systemic risk tool in the EU to monitor AI-based credit concentration or procyclicality at the market level on the same level as macroprudential banking supervisor instruments). Second, there is a higher level of governance gaps in the emerging markets since regulatory capacity in the emerging markets is the least, and the populations that are the most vulnerable to the inclusion-bias paradox are concentrated in the emerging markets. This imbalance requires global coordination with the FSB and Basel Committee to avoid a global AI credit governance system that will be based on two levels, where the most vulnerable groups will be least safeguarded.

VI. CONCLUSION

6.1 Summary of Findings

The paper summarizes 30 peer-reviewed articles on the topic of AI-based credit risk assessment in fintech lending that came up with findings in four dimensions. Ensemble and hybrid XAI models offer economic material benefits to traditional scorecards on model performance, yet the performance hierarchy is coupled with interpretability shortcomings that pose real regulatory problems that arise in adverse-action jurisdictions. On financial inclusion, AI credit systems expand access rates to thin-file and unbanked borrowers by significant percentages in new markets, but inherent contradictions of digital inclusion, AI-driven pricing bias, and excessive leverage constrain and even hinder the potential of inclusion. Three new propagation pathways at the intersection of credit and financial market interconnections driven by AI: model herding, procyclicality, and platform contagion, give rise to systemic vulnerability and are left unaddressed by current prudential frameworks in detecting and mitigating them. Regarding regulatory governance, the world market is divided and unbalanced, with jurisdictional and the [23] skewing to best practice without addressing the systemic risk aspect, and new markets experiencing the greatest governance gap.

6.2 Theoretical Contributions

Three main contributions are promoted. To start with, the IACRF offers a novel multi-level governance architecture to combine the SAFE AI imperatives and the fintech credit lifecycle in five stages of operation, filling the uncharted gap in frameworks that jointly focus on model-level performance and fairness, firm-level compliance, and market-level systemic risk. Second, a theoretically-based taxonomy of systemic risk propagation pathways that are particular to AI-powered fintech lending is introduced that builds on the connectedness framework by [7] in the algorithmic credit environment. Third, the theory of information asymmetry, the theory of financial innovation, and the SAFE AI framework are brought into a consistent analytical framework that proves these traditions to be mutually reinforcing and how integrating them brings insights into governance that none can bring forth alone.

6.3 Policy Recommendations

There are four sets of recommendations that are promoted. To regulators and central banks: AI credit models with more than a specified level of deployment should be required to have explainability and an independent bias audit, coordinated by the Basel Committee and FSB, to avoid regulatory arbitrage; systemic

risk observation of AI-driven credit concentration and model herding should be included in the macroprudential surveillance frameworks. In the case of fintech companies, embracing the IACRF or a similar governance framework must be considered a prerequisite to a regulatory license in highly-regulated AI jurisdictions, and there should be a model risk officer and fairness engineering position on credit risk teams. In the case of multilateral development institutions, to avoid increasing digital divides and the emergence of unregulated AI credit markets where governments lack the capacity to regulate, specific funding in the digital infrastructure, financial literacy, and capacity building in emerging markets is important. In the case of the academic community, longitudinal empirical research and tracking of the accuracy and bias of AI credit models across the full economic cycles, and quantitative models of the systemic risk propagation in AI-mediated lending networks are the most urgent research priorities.

6.4 Limitations and Future Research

There are three limitations in the paper. The use of published literature restricts causal inference and evaluation of unpublished industry practices; the literature that is reviewed is likely to suffer from publication bias that would bias towards positive results of model performance. IACRF is theoretically based, but it is yet to be supported by empirical research (field) and case studies of practitioners. The fast-changing regulatory environment will imply that particular references might have to be updated when the implementation of the AI Act in the EU and the FSB AI guidance is complete. The IACRF should be empirically tested in different fintech settings in future research, and longitudinal studies of AI credit models' performance in economic cycles and network-based empirical models of the propagation of systemic risk in AI-mediated lending markets should be developed.

6.5 Concluding Remarks

FinTech lending credit risk assessment based on AI is a revolution that can be governable, but its effects on society depend on the governance models that govern its implementation. The IACRF, which will be suggested in this paper, is a step towards establishing such frameworks - a collaborative project that requires the participation of computer scientists, economists, lawyers, regulators, development practitioners, and communities impacted. The AI governance in credit markets is not an issue of a technical nature and has a technical solution; it is an institutional issue that requires institutional innovation in the interface of technology, finance, and democratic accountability.

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