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Explainable AI in Credit Decisioning: Balancing Accuracy and Transparency

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Abstract

The integration of artificial intelligence (AI) into credit decisioning has significantly enhanced the accuracy and efficiency of credit risk assessment, enabling financial institutions to process vast volumes of applicant data and detect complex patterns beyond the capacity of traditional statistical models. However, the growing reliance on high-performance yet opaque "black box" algorithms, such as deep learning and ensemble methods, has raised concerns over interpretability, fairness, and regulatory compliance. Explainable AI (XAI) emerges as a critical paradigm for addressing these challenges, offering methodologies that make model outputs understandable to both technical and non-technical stakeholders without undermining predictive performance. This examines the inherent trade-off between accuracy and transparency in AI-driven credit scoring, analyzing the capabilities and limitations of interpretable models (e.g., logistic regression, decision trees) and model-agnostic explanation techniques (e.g., LIME, SHAP, counterfactual analysis). This situates XAI within the context of legal frameworks such as the EU's General Data Protection Regulation (GDPR) "Right to Explanation" and the Basel Committee's risk management principles, emphasizing its role in fostering trust, mitigating bias, and supporting fair lending practices. Case studies from banking and fintech sectors illustrate practical implementations, demonstrating how hybrid approaches can preserve the benefits of advanced machine learning while meeting transparency requirements. Challenges remain, including explanation fidelity, scalability, and alignment between technical justifications and regulatory expectations. The findings suggest that adopting XAI in credit decisioning is not only feasible but also strategically advantageous for improving customer confidence, enhancing compliance, and promoting responsible innovation in financial services. Future research should focus on developing standardized explainability metrics, advancing interpretable deep learning, and embedding XAI into governance frameworks to balance the dual imperatives of accuracy and transparency.

Keywords: Explainable AI, Credit Decisioning, Accuracy, Transparency

1. Introduction

The financial sector has witnessed a rapid integration of Artificial Intelligence (AI) and Machine Learning (ML) techniques in credit scoring and loan approval processes (Adeshina and Poku, 2025 [8]; Dogho, 2025). These technologies have transformed traditional risk assessment models by enabling lenders to process vast amounts of structured and unstructured data, identify complex nonlinear relationships, and improve the precision of creditworthiness evaluations (Dogho, 2025; Obioha *et al*., 2025). Advanced algorithms, such as deep neural networks and gradient boosting machines, have demonstrated superior predictive accuracy compared to conventional statistical models, thereby enhancing loan portfolio performance and reducing default rates (Obioha *et al*., 2025; Adeshina *et al*., 2025 [9]). However, as financial institutions increasingly rely on such high-performance models, they face the growing challenge of aligning these innovations with regulatory mandates and ethical obligations that prioritize transparency, fairness, and accountability. Regulatory frameworks, including the General Data Protection Regulation (GDPR) in the European Union and the Equal Credit Opportunity Act (ECOA) in the United States, emphasize the right of individuals to receive understandable explanations for automated decisions (Balogun *et al*., 2025; Olisa, 2025) [24, 61]. This dual imperative—maximizing model accuracy while ensuring interpretability—has emerged as a central

tension in AI-driven credit decisioning.

While highly sophisticated AI models have delivered unprecedented gains in predictive accuracy, many operate as "black boxes," producing outputs that are difficult for humans to interpret or audit (Ogunmolu *et al*., 2025 [56]; Dogho, 2025). Deep learning architectures and ensemble techniques, though powerful, often obscure the decision logic behind credit approvals or rejections. This opacity raises significant concerns for regulators, financial institutions, and consumers. From a compliance standpoint, opaque decision-making processes risk violating legal requirements for explainability, particularly in cases of adverse credit decisions. From an ethical perspective, a lack of interpretability can conceal biases embedded in training data, perpetuating discriminatory outcomes against vulnerable groups (Dogho, 2025; Annan *et al*., 2025 [20]). Consequently, the inability to explain AI-generated credit decisions undermines trust in the financial system and may impede the broader adoption of AI in lending (Annan *et al*., 2025 [20]; Dogho, 2025).

The objective of this, is to explore strategies and frameworks that enhance the explainability of AI-driven credit decision models without substantially compromising their predictive performance. This involves evaluating existing Explainable AI (XAI) techniques—such as SHapley Additive exPlanations (SHAP), Local Interpretable Model-agnostic Explanations (LIME), counterfactual analysis, and inherently interpretable models—and assessing their suitability for real-world credit risk environments. The research seeks to identify best practices that enable institutions to maintain high accuracy in credit scoring while providing stakeholders with clear, actionable, and compliant explanations of model behavior.

Explainable AI (XAI) frameworks present a viable pathway to harmonize predictive accuracy with regulatory and ethical transparency in credit decisioning. By integrating model-agnostic interpretability methods, bias detection tools, and transparent reporting mechanisms, financial institutions can foster greater trust among borrowers, meet compliance requirements, and promote equitable access to credit. Achieving this balance is not merely a technical challenge but a strategic imperative for the sustainable deployment of AI in financial services (Fasasi *et al*., 2024; Adebowale and Ashaolu, 2024) [38, 4]. This argues that well-designed XAI systems can preserve the competitive advantages of advanced predictive models while ensuring decisions remain understandable, auditable, and fair—thereby enhancing both operational effectiveness and societal trust in AI-driven lending.

2. Methodology

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework was applied to conduct a comprehensive and transparent literature review on explainable artificial intelligence (XAI) in credit decisioning, with a focus on balancing accuracy and transparency. The search strategy was designed to identify peer-reviewed journal articles, conference papers, and industry reports published between 2010 and 2025, ensuring coverage of both foundational theories and recent advancements. Electronic databases including Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar were searched using Boolean combinations of keywords such as "explainable AI," "credit scoring," "loan decisioning," "model interpretability," "LIME," "SHAP," "counterfactual explanations," "financial transparency," and "accuracy vs interpretability." Additional records were identified through citation tracking and reference list screening of relevant publications.

The inclusion criteria comprised studies that applied or evaluated XAI techniques in credit scoring or lending decisions, addressed the trade-off between model performance and interpretability, and provided empirical or simulation-based evidence. Exclusion criteria eliminated works unrelated to credit decisioning, purely theoretical papers without application, and studies not available in English. After duplicate removal, the remaining articles were screened based on titles and abstracts, followed by full-text assessments to determine relevance. Data extraction captured study context, AI methods used, XAI techniques applied, evaluation metrics, regulatory considerations, and reported challenges.

The screening process followed the PRISMA flow, starting with initial retrieval of 1,276 records, reduction to 842 after duplicate removal, exclusion of 613 during title/abstract screening, and final inclusion of 65 studies for qualitative synthesis. The selected literature was analyzed thematically to identify prevailing XAI approaches in credit decisioning, trade-off management strategies, regulatory compliance considerations, and emerging research gaps. This systematic process ensured methodological rigor, minimized bias, and provided a robust evidence base for evaluating how XAI can support fair, transparent, and accurate credit decision-making.

2.1 Theoretical Foundations

Artificial Intelligence (AI) and Machine Learning (ML) have transformed the credit decisioning landscape by enabling financial institutions to evaluate applicant creditworthiness with unprecedented accuracy and efficiency (Umoh *et al*., 2024 [67]; Nwokediegwu *et al*., 2024). The theoretical basis of these systems encompasses three key dimensions: the evolution from traditional statistical models to complex ML algorithms, the conceptualization of explainability within AI systems, and the regulatory frameworks shaping their development and deployment.

Historically, credit risk assessment relied heavily on statistical models, particularly logistic regression and linear discriminant analysis. These models offered clear interpretability, with coefficients directly indicating the influence of predictor variables such as income, debt-to-income ratio, and payment history on credit risk (Nwokediegwu *et al*., 2024; Abatan *et al*., 2024 [1]). Their simplicity, transparency, and ease of regulatory audit made them the standard in banking for decades. However, they were limited in handling non-linear relationships, high-dimensional datasets, and complex feature interactions, often leading to suboptimal predictive accuracy.

The advent of machine learning introduced more powerful algorithms, including decision trees, random forests, gradient boosting machines (GBMs), and neural networks. These models excel at capturing non-linearities and variable interactions, leveraging large and diverse datasets such as transaction histories, geolocation data, and alternative credit signals. As a result, predictive performance in credit decisioning significantly improved, with reduced default rates and more accurate identification of creditworthy

individuals (Okon *et al*., 2024; Joeaneke *et al*., 2024) [60, 43]. Nonetheless, this shift toward algorithmic sophistication introduced a major challenge: reduced interpretability. The so-called "black box" nature of many ML models made it difficult for both regulators and customers to understand the rationale behind a credit decision.

Explainability in AI refers to the degree to which the internal mechanics of a model and the rationale for its outputs can be understood by humans. It is often differentiated from interpretability, where interpretability implies inherent simplicity of the model (as in linear regression), while explainability involves external methods to elucidate the decision-making process of complex models (Ibekwe *et al*., 2024; Dada *et al*., 2024). The key principle is that stakeholders—whether data scientists, regulators, or end-users—must be able to comprehend why a given decision was made, especially in high-stakes domains such as lending.

Two broad categories of explanations are relevant in credit decisioning: global and local. Global explanations provide an overarching view of the model's logic, identifying the most influential features across all decisions. This can reveal, for example, that payment history and income stability are consistently the most significant drivers of credit approval. Local explanations, on the other hand, focus on individual decisions, clarifying why a specific applicant was approved or rejected. Techniques such as SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) have become prominent tools for producing such insights. Global explanations support model governance and compliance, while local explanations enhance customer transparency and appeal processes.

The integration of AI into credit decisioning is governed by a complex interplay of international, regional, and national regulations designed to ensure fairness, accountability, and transparency (Etukudoh *et al*., 2024; Ibekwe *et al*., 2024). Basel III, while primarily concerned with capital adequacy and systemic risk management, indirectly influences credit decisioning by emphasizing robust risk assessment practices. AI-driven models used in credit risk evaluation must align with Basel III principles of sound risk governance, model validation, and operational resilience.

In the European Union, the General Data Protection Regulation (GDPR) introduces a "Right to Explanation," which, while debated in its precise scope, underscores the requirement that individuals subject to automated decisions can request meaningful information about the logic involved (Selesi-Aina *et al*., 2024; Asonze *et al*., 2024) [66, 22]. This provision is particularly relevant in the context of opaque ML models, compelling institutions to adopt XAI techniques that translate algorithmic outputs into human-understandable terms.

Local banking compliance frameworks also play a significant role. In the United States, the Equal Credit Opportunity Act (ECOA) and the Fair Credit Reporting Act (FCRA) mandate non-discrimination and the provision of adverse action notices explaining the main reasons for credit denial. Similar mandates exist in many jurisdictions, where consumer protection agencies require clear communication of decision rationale, whether the model is statistical or AI-based (Nwokediegwu *et al*., 2024; Etukudoh *et al*., 2024). The growing adoption of AI has prompted regulators to propose or enforce guidelines on ethical AI usage, bias mitigation, and continuous model monitoring.

Together, these regulatory regimes create both an obligation and an opportunity for financial institutions to integrate explainability into their AI credit decisioning systems. Failure to meet transparency requirements can lead to legal penalties, reputational damage, and erosion of customer trust. Conversely, effective integration of XAI principles can enhance stakeholder confidence, improve compliance readiness, and differentiate institutions in increasingly competitive lending markets (Akinola *et al*., 2024; Aniebonam, 2024) [15, 18].

The theoretical foundations of explainable AI in credit decisioning rest on the historical evolution from transparent but limited statistical models to complex but opaque ML algorithms, the conceptual framework distinguishing interpretability from explainability, and the regulatory imperatives shaping system design. Understanding these foundations is essential for designing AI-driven credit decisioning systems that not only optimize predictive accuracy but also uphold the principles of fairness, transparency, and accountability that are critical to sustainable financial services (Obiuto *et al*., 2024 [54]; Nwokediegwu *et al*., 2024).

2.2 Trade-Off Between Accuracy and Transparency

In AI-driven credit decisioning, one of the most persistent challenges is the trade-off between model accuracy and interpretability. This dilemma arises because models that achieve the highest predictive accuracy often do so through highly complex architectures that resist human understanding (Nwokediegwu *et al*., 2024; Dada *et al*., 2024). For example, decision trees, which represent a set of rules in a hierarchical structure, are easily interpretable; a lender can trace a borrower's approval or rejection directly to specific conditions, such as income thresholds or credit utilization ratios. However, while decision trees offer clarity, their predictive performance on large, high-dimensional datasets is often inferior to that of more advanced methods.

Gradient boosting machines (GBMs), by contrast, combine multiple weak learners—typically decision trees—into a powerful ensemble model capable of capturing subtle, nonlinear patterns in the data. This results in significantly higher accuracy and robustness, especially in environments where credit risk factors interact in complex ways. The trade-off is that GBMs produce thousands of interdependent decision rules, making it practically impossible to intuitively explain the reasoning behind a specific prediction without specialized tools. Thus, while decision trees excel in transparency, GBMs outperform in predictive power, illustrating the tension between interpretability and performance in credit scoring systems.

For lenders, accuracy in credit scoring is critical for minimizing default risk and optimizing portfolio returns. High-performing models like GBMs or deep learning architectures allow lenders to better differentiate between low- and high-risk borrowers, which can translate into reduced non-performing loan ratios and improved profitability. However, when these models are opaque, operational risks arise. In the event of disputes or adverse credit decisions, lenders may be unable to provide satisfactory explanations, potentially exposing them to legal challenges and reputational harm (Ilojianya *et al*., 2024 [42]; Nwokediegwu *et al*., 2024). Moreover, reliance on black-

box models can impede internal risk audits, making it harder to identify systemic biases or data drift. Consequently, lenders must weigh the benefits of superior accuracy against the operational and compliance risks introduced by reduced interpretability.

From the borrower's perspective, transparency is essential to trust and fairness in the credit process. Clear explanations help individuals understand which factors contributed to their approval or rejection, enabling them to take corrective actions, such as reducing outstanding debt or improving repayment histories. When decisions are derived from opaque models, borrowers are often left in the dark, which can lead to perceptions of unfair treatment or discrimination. In jurisdictions with strong consumer protection laws, such as under the GDPR's "right to explanation," the inability to provide understandable reasons can result in regulatory violations. Furthermore, a lack of interpretability may exacerbate the financial exclusion of marginalized groups if systemic biases in the data are hidden within complex models.

For regulators, the priority is ensuring that automated credit decisions adhere to legal standards for fairness, non-discrimination, and accountability. Black-box models present significant challenges in this regard because they hinder the ability to audit and verify compliance. Regulatory bodies require that lenders not only demonstrate the statistical validity of their credit scoring systems but also provide comprehensible justifications for individual decisions. This is especially relevant in detecting disparate impact, where certain demographic groups may be disproportionately affected by model predictions. Transparent models, even if slightly less accurate, offer greater auditability, facilitating investigations and fostering public confidence in the financial system (Ayorinde *et al*., 2024 [23]; Nwokediegwu *et al*., 2024). Regulators are increasingly advocating for or mandating the use of Explainable AI (XAI) techniques to bridge the gap, ensuring that lenders can both achieve high performance and meet transparency requirements.

The trade-off between accuracy and transparency is not necessarily a zero-sum game. Recent advances in XAI techniques, such as SHAP and LIME, allow stakeholders to extract interpretable insights from complex models without significantly degrading performance. These tools can decompose individual predictions into contributions from specific variables, making even GBMs more transparent to end-users and regulators. Hybrid modeling approaches, where an interpretable model is used for decision justification while a high-performing model handles prediction, also offer a potential compromise. Nonetheless, the effectiveness of such strategies depends on their integration into both the technical and operational workflows of lending institutions.

Ultimately, the performance–interpretability dilemma is not just a technical issue but a strategic one that affects risk management, regulatory compliance, and consumer trust. The ability to navigate this trade-off effectively will determine how well AI-powered credit decisioning systems can be deployed sustainably in the financial sector.

2.3 Explainable AI Techniques for Credit Decisioning

The need to reconcile predictive accuracy with transparency in credit decisioning has led to the development of a range of explainable AI (XAI) techniques. These techniques can be classified into three broad categories: model-specific approaches that are inherently interpretable, model-agnostic methods that explain any model post hoc, and hybrid approaches that integrate the predictive strength of complex algorithms with interpretable surrogates as shown in figure 1 (Alahira *et al*., 2024 [17]; Akerele *et al*., 2024).

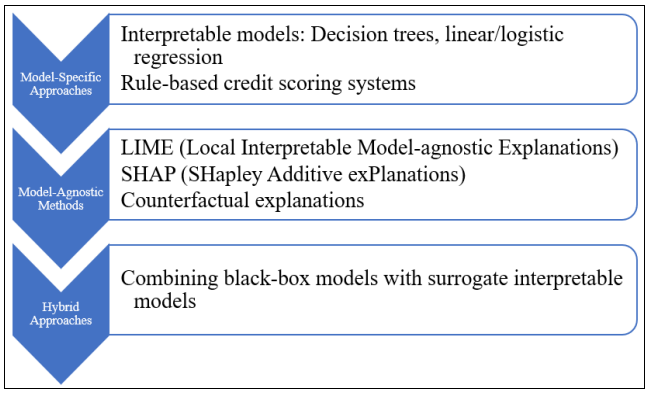

Fig 1: Explainable AI Techniques for Credit Decisioning

Model-specific approaches rely on algorithms whose internal decision logic is inherently understandable to humans. Decision trees are a prominent example, representing decisions as a series of hierarchical splits on predictor variables. In credit decisioning, a decision tree might first assess whether an applicant's debt-to-income ratio exceeds a certain threshold, followed by checks on payment history or credit utilization. Their visual structure allows stakeholders to trace the path from input variables to output, aiding compliance with regulatory requirements for clear explanations. However, overly deep trees can become complex, reducing interpretability.

Linear and logistic regression models have been historically dominant in credit scoring due to their transparency. Coefficients directly indicate the direction and magnitude of a variable's influence on the likelihood of default, enabling lenders to articulate reasons for approval or denial in straightforward terms. Logistic regression, in particular, has been widely used for binary credit decisions, translating well into regulatory contexts requiring clear adverse action notices (Ojukwu *et al*., 2024; Uzoka *et al*., 2024).

Rule-based credit scoring systems extend the idea of model-specific transparency by encoding domain knowledge as a set of "if–then" conditions. For instance, "If credit score < 600 and annual income < $25,000, then reject" offers complete clarity on decision logic. Such systems align well with compliance demands and facilitate manual overrides when needed. However, their predictive performance may lag behind modern machine learning algorithms, particularly in complex, non-linear problem spaces.

Model-agnostic XAI techniques operate independently of the underlying algorithm, making them applicable to both simple and highly complex "black box" models. Local Interpretable Model-agnostic Explanations (LIME) is one such method. LIME approximates a model's decision boundary locally around a specific instance using a simpler, interpretable model such as a linear regression. In credit decisioning, LIME can explain why a gradient boosting machine rejected an application by highlighting the most influential features—e.g., high credit utilization and recent delinquencies—specific to that applicant.

SHapley Additive exPlanations (SHAP) build on cooperative game theory to assign each feature a contribution score for an individual prediction. Unlike LIME, SHAP provides consistency and local accuracy, ensuring that the sum of feature contributions matches the model output. In lending contexts, SHAP can reveal that a low income contributes negatively to creditworthiness by a precise percentage, while a long repayment history contributes positively, thus offering nuanced and quantitative insights (Uzoka *et al*., 2024; Ojukwu *et al*., 2024).

Counterfactual explanations focus on providing applicants with actionable insights by showing minimal changes needed to achieve a different decision outcome. For example, a counterfactual might state, "If your monthly debt payments were $200 lower, your application would have been approved." This approach empowers consumers with clear pathways to improve their eligibility while satisfying transparency and fairness requirements.

Hybrid approaches aim to capture the best of both worlds by combining the predictive power of complex models with the interpretability of simpler surrogates. One strategy involves training a high-performing model, such as an ensemble method or deep neural network, for primary decision-making, and then fitting an interpretable surrogate model—such as a decision tree or rule list—on its predictions (Ikwuanusi *et al*., 2024 [41]; Akerele *et al*., 2024). The surrogate approximates the complex model's behavior, providing global or local explanations while preserving performance.

In credit decisioning, hybrid systems can use a gradient boosting model for accurate risk prediction and a shallower decision tree as a surrogate for explanation to regulators or customers. This enables institutions to maintain competitive advantage in predictive accuracy without sacrificing auditability. Another hybrid variant incorporates model-agnostic tools such as SHAP or LIME into production workflows, ensuring that every credit decision is accompanied by an interpretable rationale.

Hybrid methods address the inherent trade-off between accuracy and transparency but introduce their own challenges, particularly ensuring that the surrogate or explanation truly reflects the complex model's reasoning. Fidelity metrics are often used to quantify how closely explanations match the underlying model's behavior, which is crucial for regulatory acceptance.

The landscape of XAI techniques for credit decisioning offers a spectrum of options, from inherently transparent models to post hoc and hybrid approaches. Model-specific methods such as decision trees and logistic regression ensure intrinsic interpretability, while model-agnostic tools like LIME, SHAP, and counterfactuals extend transparency to complex models (Akerele *et al*., 2024; Owoade *et al*., 2024). Hybrid strategies enable institutions to leverage advanced machine learning capabilities while meeting regulatory and ethical demands for transparency. Selecting the appropriate approach requires balancing predictive accuracy, compliance requirements, operational constraints, and the need to foster trust among consumers and regulators alike.

2.4 Case Studies and Applications

In the banking sector, gradient boosting machines (GBMs) have become a preferred choice for credit scoring due to their high predictive accuracy. However, their complexity often limits interpretability (Ojukwu *et al*., 2024; Uzoka *et al*., 2024). One notable application addressing this limitation involves the use of SHapley Additive exPlanations (SHAP) to interpret GBM outputs. SHAP is a model-agnostic explainability framework derived from cooperative game theory, which assigns each feature a contribution value representing its impact on a particular prediction.

A leading European retail bank implemented a GBM model trained on thousands of borrower attributes—ranging from credit bureau scores and repayment histories to transactional patterns—to enhance default risk prediction. To comply with the EU's General Data Protection Regulation (GDPR) and internal risk governance standards, SHAP was integrated into the model deployment pipeline. This allowed credit officers to generate per-customer explanation reports detailing how each feature influenced the loan decision. For example, a rejected loan application could be explained by a combination of high credit utilization (+0.25 SHAP score contribution to risk), recent late payments (+0.18), and insufficient income documentation (+0.12). These transparent, quantitative attributions enabled the bank to satisfy regulatory audits, improve internal model validation, and provide borrowers with clear, actionable feedback. Importantly, the use of SHAP preserved the high predictive performance of the GBM, illustrating that explainability need not come at the cost of accuracy.

In the fintech sector, mobile lending platforms have disrupted traditional credit markets by offering rapid, often near-instant loan approvals based on alternative data sources (Akerele *et al*., 2024; Owoade *et al*., 2024). These may include smartphone metadata, digital payment histories, and social network behavior. While such models—often powered by ensemble methods or deep learning—achieve impressive accuracy, their opacity can hinder user trust, especially in emerging markets where financial literacy varies widely.

A case in point is a Southeast Asian fintech company that deployed an explainable credit scoring system using a real-time LIME (Local Interpretable Model-agnostic Explanations) framework. LIME approximates complex models locally with simpler interpretable models, enabling fast, context-specific explanations for each decision. When a borrower applies for a loan via the mobile app, the system generates an immediate breakdown of key approval factors—e.g., "consistent mobile wallet deposits" (+0.20) and "low missed payment ratio" (+0.15)—or rejection factors—e.g., "high recent spending relative to income" (+0.22). These explanations are displayed in-app within seconds, alongside tailored recommendations for improving creditworthiness.

This transparency mechanism not only helped the fintech comply with regional consumer protection laws but also enhanced customer engagement. Borrowers reported higher satisfaction rates, even when rejected, because they understood the rationale and could work towards meeting lending criteria (Owoade *et al*., 2024; Akerele *et al*., 2024). Moreover, the company observed a reduction in repeat rejections, as applicants acted on feedback to improve their financial profiles.

Empirical evidence from both banking and fintech applications suggests that transparency in credit decisioning significantly influences borrower trust, acceptance rates, and overall customer satisfaction. When borrowers receive clear,

data-driven explanations, they are more likely to perceive the lending process as fair, even in cases of rejection. This perception of fairness fosters long-term loyalty and can encourage borrowers to reapply after addressing identified risk factors.

In the European bank example, surveys indicated that customer trust scores increased by over 15% following the introduction of SHAP-based explanations. This boost in trust correlated with higher engagement rates, as borrowers were more willing to share additional financial information for reassessment. Similarly, the Southeast Asian fintech reported a measurable increase in loan acceptance rates after implementing LIME-driven transparency, attributed to reduced hesitation among potential applicants who felt they could better predict and influence their loan outcomes.

From a regulatory perspective, transparent credit scoring models also mitigate compliance risks, reducing the likelihood of disputes and enabling smoother audit processes. For lenders, this dual benefit—enhanced borrower trust and reduced legal exposure—translates into stronger brand reputation and more sustainable lending operations (Owoade *et al*., 2024; ADESHINA and NDUKWE, 2024 [7]).

Overall, these case studies underscore that integrating explainability tools such as SHAP and LIME into credit scoring systems can create a virtuous cycle: transparency drives trust, trust boosts borrower engagement, and engagement leads to more accurate, data-rich lending decisions. By demonstrating that high accuracy and interpretability can coexist, these applications provide a blueprint for responsible AI adoption in credit decisioning.

2.5 Challenges and Limitations

While explainable AI (XAI) offers a pathway to making complex credit decisioning systems more transparent, its implementation in real-world financial environments is fraught with technical, ethical, and regulatory challenges (Fasasi *et al*., 2023; Nwokediegwu and Adebowale, 2023 [51]). These limitations highlight the difficulty of balancing accuracy, interpretability, and compliance in a domain where decisions carry high stakes for individuals and institutions alike as shown in figure 2.

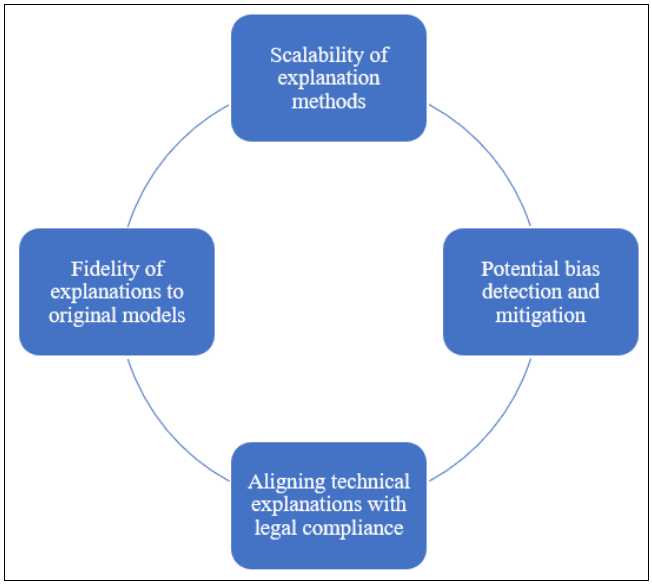

Fig 2: Challenges and Limitations

One of the foremost technical challenges in applying XAI to credit decisioning is scalability. Many explanation methods, particularly model-agnostic ones such as SHAP and LIME, are computationally intensive. For large-scale lending platforms that process thousands or millions of applications daily, generating explanations for each decision can impose significant computational and latency costs. This is especially problematic for real-time credit approval systems, such as those used in online lending and mobile banking, where processing delays could disrupt customer experience and operational efficiency. Scaling explanation algorithms without degrading performance remains an active area of research, involving trade-offs between precision, speed, and resource usage.

Fidelity of explanations to the original model is another critical issue. Explanations, especially those derived from surrogate models or local approximations, may not perfectly reflect the decision-making process of the underlying "black box" model. A surrogate decision tree may capture broad patterns but miss subtle interactions that the original neural network or ensemble model relies upon. Low-fidelity explanations risk misleading stakeholders, undermining trust, and exposing institutions to regulatory challenges if explanations do not accurately match the true model logic (Fasasi *et al*., 2023; Crawford *et al*., 2023 [25]). Developing metrics and standards for explanation fidelity is essential to ensure that interpretability does not come at the cost of truthfulness.

Ethical concerns in XAI for credit decisioning center on bias detection and mitigation. While explanation tools can illuminate patterns in model behavior, they can also reveal discriminatory effects embedded in training data or learned from historical lending practices. For example, SHAP values might show that postcode or occupation is disproportionately influencing credit denials, indirectly encoding socioeconomic or demographic biases. Identifying such biases is only the first step; mitigation often requires retraining models, altering feature sets, or applying fairness constraints, all of which can impact accuracy and operational viability.

Moreover, there is a tension between transparency and privacy. Providing detailed explanations may inadvertently expose sensitive information, either about the applicant or about proprietary model features. Financial institutions must balance the ethical imperative to explain decisions with the need to protect customer privacy and safeguard competitive intellectual property.

Regulatory compliance is both a driver and a constraint for XAI in credit decisioning. Laws such as the EU's General Data Protection Regulation (GDPR), the U.S. Equal Credit Opportunity Act (ECOA), and the Fair Credit Reporting Act (FCRA) impose requirements for providing meaningful explanations of automated decisions. However, these legal mandates often lack precise definitions of "meaningful," leaving institutions uncertain about the level of technical detail required. Aligning the output of XAI tools with regulatory expectations can therefore be challenging, especially in jurisdictions where enforcement guidelines are evolving.

Operationally, integrating XAI into existing lending workflows demands significant changes in system architecture, staff training, and governance procedures. Risk management teams, compliance officers, and customer

service representatives must be able to interpret and communicate explanations effectively, requiring cross-disciplinary expertise. In many cases, the adoption of XAI also necessitates new audit and monitoring processes to ensure that explanations remain accurate as models are retrained and updated (Abdulsalam *et al*., 2021; Ogeawuchi *et al*., 2021) [2, 55]. These operational adjustments can be resource-intensive, particularly for smaller institutions or fintech start-ups with limited compliance infrastructure.

Furthermore, regulators may require consistency between technical explanations and consumer-facing narratives. A technically precise explanation might involve complex statistical reasoning that is incomprehensible to the average applicant, while a simplified explanation risks omitting important details. Striking a balance between accuracy, clarity, and legal defensibility is a persistent operational challenge.

The promise of explainable AI in credit decisioning is counterbalanced by substantial challenges. Technical limitations such as scalability and explanation fidelity can hinder deployment at scale, while ethical concerns about bias and privacy complicate the pursuit of fairness. Regulatory ambiguity and operational demands add further layers of complexity. Addressing these challenges will require advances in efficient, high-fidelity explanation techniques, robust bias mitigation strategies, and clearer regulatory guidance, alongside organizational investment in training and governance. Without such measures, the adoption of XAI in credit decisioning risks remaining partial, failing to achieve its potential to enhance both accuracy and transparency in financial services (UZOKA *et al*., 2021; Adebowale and Nwokediegwu, 2022) [71, 3].

2.6 Future Directions

While traditional machine learning methods such as decision trees and logistic regression have long been favored for their interpretability, deep learning models are increasingly being explored for credit scoring due to their ability to process vast and heterogeneous datasets as shown in figure 3. Historically, the major limitation of deep neural networks (DNNs) in financial decisioning has been their opacity. However, emerging advances in interpretable deep learning are beginning to challenge this perception (Adebowale and Etukudoh, 2022; Akpe *et al*., 2022 [16]). Techniques such as attention mechanisms, prototype learning, and layer-wise relevance propagation (LRP) enable granular inspection of a network's decision-making process.

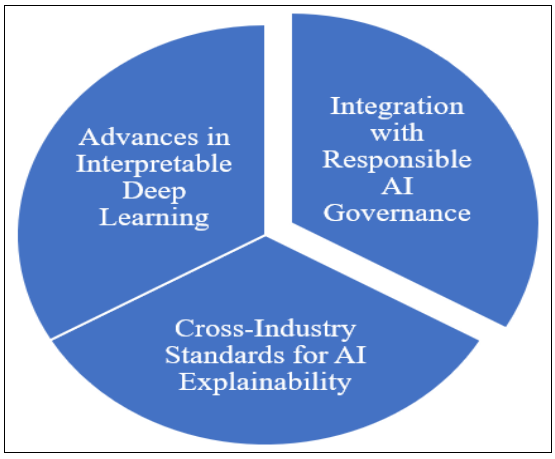

Fig 3: Future Directions

In credit risk assessment, attention-based neural networks can highlight which parts of a borrower's financial history the model focuses on when making predictions, offering human-readable rationales for approvals or rejections. Similarly, concept-based interpretability approaches—such as Testing with Concept Activation Vectors (TCAV)—allow models to explain predictions in terms of high-level, domain-relevant concepts (e.g., "payment punctuality" or "credit utilization stability") rather than raw numerical features. As these interpretability-enhancing architectures mature, they may bridge the gap between the predictive strength of deep learning and the explainability needed for regulatory and ethical compliance in lending.

Future adoption of Explainable AI (XAI) in credit decisioning will increasingly be shaped by Responsible AI (RAI) governance frameworks. RAI encompasses not only transparency but also fairness, accountability, privacy, and human oversight. Integrating explainability into these broader governance systems ensures that interpretability is not treated as an isolated technical add-on but as a core principle embedded in the entire AI lifecycle—from data collection and model development to deployment and monitoring (Annan, 2021 [21]; Adebowale and Etukudoh, 2022).

For example, financial institutions could adopt governance models where every deployed credit scoring algorithm undergoes pre-launch explainability audits, assessing both the clarity of model outputs and the robustness of interpretability tools such as SHAP or LIME. Post-deployment, these models could be continuously monitored for drift, bias emergence, and explanation consistency. Regulatory bodies, in turn, could mandate periodic third-party audits of both predictive and explanatory performance. Embedding explainability into RAI frameworks also supports human-in-the-loop systems, where credit officers can override automated decisions when explanations indicate possible errors or fairness concerns. This combination of automation and oversight may be critical for preserving trust in AI-driven credit processes.

One of the current challenges in explainable credit decisioning is the lack of consistent standards across institutions and jurisdictions. While certain regulations, such as the GDPR and the Equal Credit Opportunity Act, require explanations for automated decisions, they do not prescribe detailed technical criteria for what constitutes a "satisfactory" explanation. This regulatory ambiguity leads to variability in how lenders implement interpretability, making it difficult to compare practices across the industry.

The future may see the emergence of cross-industry standards for AI explainability, developed collaboratively by regulators, industry consortia, and academic bodies. Such standards could define metrics for explanation quality—e.g., fidelity (how closely the explanation reflects the underlying model), comprehensibility (ease of understanding by non-experts), and actionability (ability to inform borrower behavior). They might also specify minimum acceptable practices for transparency reporting, bias detection, and feature attribution in credit scoring.

For instance, a standard might require that any automated loan decision be accompanied by a ranked list of the top five contributing factors, quantified in their impact on the decision, and presented in plain language. Another possible requirement could be the public disclosure of model classes and interpretability methods used, without revealing

proprietary model weights. Cross-industry explainability standards would not only harmonize compliance expectations but also enable fairer competition, as all lenders would operate under the same transparency benchmarks.

The trajectory of AI in credit decisioning points toward an ecosystem where accuracy and transparency coexist by design rather than trade-off. Advances in interpretable deep learning promise to extend the reach of high-performance models into domains that demand strict accountability. Integration with Responsible AI governance will ensure that explainability becomes an operational norm, not a regulatory afterthought (Dogho, 2021; Dogho, 2023) [29, 30]. Meanwhile, cross-industry standards will provide a shared language for transparency, enhancing comparability, fairness, and public trust.

If successfully implemented, these developments could mark a shift from explainability as a compliance burden to explainability as a competitive advantage—one that not only satisfies regulators but also strengthens borrower relationships and drives sustainable growth in the financial sector. In this future, explainable AI will not simply explain credit decisions; it will redefine the principles by which those decisions are made.

3. Conclusion

The examination of explainable AI (XAI) in credit decisioning demonstrates that achieving a balance between predictive accuracy and transparency is both feasible and strategically advantageous. Advances in interpretable modeling, model-agnostic explanation tools, and hybrid approaches provide practical pathways for integrating high-performing machine learning systems with mechanisms that make their decisions understandable to stakeholders. While the transition from traditional statistical models to complex AI algorithms has introduced interpretability challenges, emerging techniques such as SHAP, LIME, and counterfactual explanations enable financial institutions to preserve transparency without substantially compromising model performance.

From a practical perspective, the adoption of XAI has far-reaching implications for the credit industry. Transparent decision-making fosters trust among borrowers, who are more likely to accept and act on credit decisions they understand. For financial institutions, explainability enhances compliance readiness by aligning outputs with regulatory requirements, reducing legal and reputational risk. Additionally, clearer communication of decision logic can contribute to greater financial inclusion, as applicants receive actionable feedback on how to improve their creditworthiness. This dual benefit—operational efficiency and social responsibility—positions XAI as a critical enabler of responsible lending in both traditional banking and fintech contexts.

Moving forward, the full realization of XAI's potential requires coordinated, interdisciplinary collaboration. Data scientists must design models with interpretability as a core feature rather than an afterthought. Regulators must provide clearer, standardized guidelines for what constitutes an adequate explanation, ensuring consistency across jurisdictions. Financial institutions must invest in governance structures, staff training, and consumer education to make explanations accessible and meaningful. By aligning technical innovation, regulatory oversight, and institutional practice, the industry can establish a credit decisioning ecosystem that is not only accurate and efficient but also fair, transparent, and inclusive—advancing both market competitiveness and public trust.

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