

A Review of AI Credit Scoring in Consumer Finance: Risks, Fairness and Governance

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Abstract:

This study examines the application of artificial intelligence (AI) in credit scoring within consumer finance, focusing on its potential benefits, risks, and governance implications. Compared with traditional credit scoring models, AI-based systems can process larger and more diverse datasets, identify complex patterns, and improve the efficiency and accuracy of credit risk assessment. However, their use also raises important concerns, including algorithmic bias, lack of transparency, data privacy risks, and challenges in regulatory oversight. Drawing on existing literature and publicly available case studies, the study discusses how AI credit scoring may affect financial inclusion, consumer protection, and institutional decision-making. It further highlights the importance of explainable AI, fairness assessment, and sound governance frameworks to ensure responsible adoption. Although the study does not conduct empirical analysis with real-world consumer finance data, it provides a conceptual understanding of the opportunities and limitations of AI credit scoring. Future research should compare traditional and AI-based models using real datasets and examine how evolving regulations shape their practical application across different markets.

Keywords: AI credit scoring; Consumer finance; Credit risk assessment; Algorithmic fairness; AI governance.

1. Introduction

1.1 Research Background

Artificial intelligence (AI) has become increasingly integrated into financial services, particularly consumer finance applications such as consumer loans, credit card approvals, online lending, and BNPL (Buy Now, Pay Later). Credit scoring is a fundamental financial process that helps banks and lenders eval-

uate borrowers' creditworthiness and make lending decisions [1]. Compared with traditional scoring methods, AI credit scoring can use broader and more diverse data sources to improve credit risk identification. However, these advantages are accompanied by concerns about algorithmic opacity, data privacy, and credit fairness, which are discussed in Section 2 [2].

1.2 Research Purpose and Research Questions

The purpose of this research is to analyze the advantages of AI credit scoring systems through a thematic narrative review, specifically focusing on their benefits, risks, fairness concerns and governance measures. It also identifies the associated challenges brought by the system and provides feasible suggestions and governance measures. Beyond analyzing its pros and cons, this paper intends to deliver actionable guidance for financial institutions to implement AI credit scoring in a responsible manner. To achieve this goal, three core research questions are proposed as follows:

- 1) How does AI credit scoring change the credit decision-making process in consumer finance?
- 2) What are the issues regarding fairness, transparency, privacy and risk control in AI credit scoring?
- 3) How can financial institutions establish a more responsible, more explainable and more manageable AI credit scoring governance framework?

These three research questions will be addressed in the following sections. Section 2 examines how AI credit scoring transforms consumer finance through its applications and associated challenges, while Section 3 discusses governance frameworks for responsible AI deployment.

1.3 Research Significance

This study has theoretical, practical, and regulatory significance. Theoretically, it reviews how AI has transformed traditional credit risk management and what concerns arise from its use in credit systems. By synthesizing research on fintech, consumer finance, and algorithmic risk governance, it provides a broader perspective on how AI is reshaping credit decisions. As a comprehensive literature review, it supplements existing discussions of fintech and algorithmic governance by connecting technological change with consumer rights and financial decision-making.

Practically, the study helps financial institutions understand both the benefits and risks of AI credit scoring. It emphasizes that institutions should improve fairness, algorithmic explainability, and consumer privacy protection rather than focus only on approval efficiency. The study is also relevant to regulators, who need governance frameworks based on transparency, explainability, and auditability to reduce algorithmic risks and protect equitable access to credit.

This paper adopts a narrative review rather than a systematic review with predefined inclusion criteria. It selectively examines representative academic studies, industry reports, and regulatory guidance to describe the current landscape of AI-driven credit assessment, identify major challenges, and propose governance measures. The scope covers credit cards, consumer loans, BNPL, and dynam-

ic credit management across major jurisdictions. This focus allows the study to link practical applications with the governance problems that emerge at different stages of credit assessment. Given the rapid development of AI technologies and regulation, a timely thematic synthesis offers practical value.

2. The Impact of AI Credit Scoring on Consumer Finance

AI credit scoring is changing the decision-making process in consumer finance significantly. It can use relative data, such as transaction records, repayment behaviors and behavior data, to evaluate consumers' credit risk more effectively [3]. This section begins with the definition and development of AI credit scoring (Section 2.1), followed by an analysis of its application scenarios in consumer finance (Section 2.2). The challenges associated with these applications are then discussed in Section 2.3.

2.1 Definition and Development of AI Credit Scoring

AI credit scoring refers to a set of assessment approaches adopted by financial institutions to evaluate consumers' creditworthiness via AI technologies including machine learning, deep learning, and natural language processing [1]. Compared to the traditional credit evaluation system, AI credit scoring can deal with a larger amount of data and more complex relationships.

In the past, credit scoring was a critical process to evaluate the credit level of borrowers or institutions to reduce the possibility of credit risk and improve decision-making, which relied on the historical records, such as FICO score, credit record, income, debt information, and human judgments [1, 4, 5]. However, the introduction of an AI scoring system changed this landscape significantly, ushering in a new era of predictive analysis based on precise algorithms and alternative data, including e-commerce consumption records, mobile usage behaviors, online payment records, and social media platform activities, etc. [5]

2.2 Application Scenarios of AI Credit Scoring in Consumer Finance

This subsection focuses on the application of AI systems in specific scenarios by providing several examples. Although the role of AI credit scoring varies across different scenarios, the overarching goal is to optimize risk identification, improve consumer experience, and control credit risk.

2.2.1 Credit Card Approval

In the credit card approval scenario, AI credit scoring can assist banks in evaluating the credit risk of applicants

more quickly. Traditional credit card approval systems heavily rely on humans' evaluation of the applicants' information about credit records and income certificates. However, AI models can deal with this information at high speed and even in real-time. Drawing on applicant's credit history, transaction records, consumption patterns and repayment records, AI models shorten approval cycles, lift decision-making efficiency and optimize customer experience simultaneously [6]. A typical example of this kind of utilization is that First Hawaiian Bank uses Zest AI's automated AI to enhance the credit risk assessment of its credit card portfolio and this system increases their approval efficiency and decreases the credit risk they face significantly [7]. However, one potential problem is that, if the model uses biased data, it may result in certain groups being more likely to be rejected, such as young people, low-income individuals, or those with less credit history.

2.2.2 Consumption Loans

Consumer loans are also an important area where AI is penetrating into financial services, mainly manifested in installment loans and online small loans. From the perspective of the consumer, they can get the result of the application for loans in real-time due to the automation of AI approval. Besides, financial institutions can also dynamically assess the probability of default based on the processed behavioral data of the applicants provided by the AI system [8]. In other words, the utilization of AI credit scoring reduces financial institutions' costs of covering bad debt. Also, it shortens waiting times for consumers, thereby improving their experience. However, if the financial institution over-relies on algorithms, "automatic loan rejection" may cause consumers' confusion about the reasons why they are rejected due to the lower transparency of the algorithm, which is negative for consumer rights protection [9].

2.2.3 BNPL (Buy Now, Pay Later)

BNPL products resemble consumer loans but feature simplified approval procedures and zero interest charges. The service enables shoppers to defer payments for purchases, which demands platforms to instantly judge users' eligibility for installment plans [10]. Thus, AI credit scoring is highly suitable for such instant approval scenarios, like e-commerce platform. Compared to the traditional approval process, AI systems can evaluate risks promptly based on consumers' historical purchase records, payment behaviors and account activity. Although BNPL improves the loan experience of customers, it can also lead to excessive borrowing by consumers, especially among young consumers who may underestimate the future repayment pressure. Thereby, the AI credit scoring system should take both the responsibilities of evaluating risks and con-

sumer protection.

2.2.4 Dynamic Credit Limit Management

AI credit scoring transforms dynamic credit limit management significantly. Traditional financial institutions usually set static credit limits for users, which are rarely adjusted after initial evaluation. However, AI systems can increase or decrease the credit limit dynamically based on the analysis of consumers' recent income, expenditure, repayment performance and consumption habits. Compared to the fixed credit limit, the dynamic credit limit becomes more flexible, helping financial institutions and banks to reduce credit risks. Nowadays, more loan companies choose a dynamic credit limit instead of a fixed one. Ant Group is a typical example. The platform will score each user based on their consumption behavior and repayment records on their credit then change their credit limits based on this score. Specifically, new users may initially be granted a lower credit limit. Subsequently, if the user maintains a good repayment habit and stable consumption behavior, the system may increase their limit [11]. However, the problem is that if the changes in the credit limit are not explained, consumers may feel that these adjustments are unfair, undermining the consumer's trust in the institution.

2.2.5 Post-loan Risk Monitoring

AI credit scoring still plays a critical role at the post-loan stage. Traditional post-loan risk monitoring relies on manual follow-up by credit officers, which suffers from strong subjectivity and inconsistent risk judgment standards. By contrast, AI can monitor the repayments of the borrower, changes in their account balance and abnormal consumption in order to identify potential risk of delay. Therefore, financial institutions can take measures, such as sending reminders to the borrower, adjusting repayment plans or enhancing manual reviews, early based on the predictive analysis [12]. The risk management strategy of Fair Isaac Corporation (FICO) suggests that AI credit scoring can not only be used for pre-loan approval, but also for post-loan risk monitoring. The strategy emphasizes the introduction of data analysis, machine learning and AI to the process of post-loan collection and risk management, which helps financial institutions continuously monitor the repayment behavior of customers in order to deal with the changing external credit environment [13]. However, it is also important to note that post-loan monitoring should not become excessive monitoring; otherwise, it would infringe upon consumers' privacy.

2.3 Main Challenges Arising from AI Credit Scoring

AI credit scoring has increased the efficiency of management for financial institutions and improved the experi-

ence of consumers. However, at the same time, because the AI model always relies on a large amount of data and complex algorithms, which make the decision-making lacks transparency and fairness. In consumer finance, credit scoring will directly influence the result of the application from the consumers, such as whether one obtains a credit card, a consumer loan and BNPL services [1, 4]. Thus, these problems are about technology and also related to consumer rights and compliance management of financial institutions. This section will discuss challenges in terms of fairness, transparency and explainability, data privacy, risk management of the model and consumer protection.

2.3.1 Challenges to Fairness

Rooted in biased historical datasets and implicit proxy variable reasoning, algorithmic discrimination creates structural unfairness in consumer credit access [14]. The AI model is trained based on historical data. If the historical credit data itself contains biases, the model may replicate or even magnify these biases. For instance, in certain regions, occupations, age groups or income brackets, people used to have fewer opportunities to obtain credit. The AI might mistakenly interpret these characteristics as indicators of high risk. In this way, although the AI model appears to make judgments based on data, the actual outcome may put certain consumer groups at a disadvantage when accessing credit services. Besides, another problem is about the proxy variable, defined as a variable that can serve as a substitute for an unobservable or unmeasurable variable, even though it is not directly related to another [15]. For AI credit scoring, although the AI model does not know the sensitive information like gender, race, age, the model is able to infer these details indirectly through factors such as address, place of consumption, and occupation type, which can lead to unfair results or put some groups at a disadvantaged position in terms of credit.

2.3.2 Challenges to Transparency and Explainability

Nonlinear machine learning logic creates an inherent black-box feature that blocks traceable explanation of credit decisions [16]. Put differently, institutions face the “Black box” problem [2]. For financial institutions, this will increase the difficulty of model management and compliance review; for consumers, it will affect their ability to understand credit decisions. In detail, consumers only know their application has been refused but without any clear explanation. Meanwhile, if the financial institution cannot provide appropriate explanations, consumers will be unable to know how to improve their credit status or file an appeal against possible errors or unfair outcomes. Therefore, improving the transparency and explainability of the AI model is critical for financial institutions because it is related to compliance.

2.3.3 Challenges to Data Privacy

The wide adoption of multi-dimensional alternative data expands the scope of user information collection and triggers widespread privacy infringement risks. Except for traditional credit records, income levels and repayment histories, the model may also utilize transaction records, consumption habits, platform behavior data and online payment data, which may contain sensitive information or unauthorized private data. Although the utilization of this data can improve the accuracy of the model prediction, it raises data privacy risks that may infringe upon consumers’ right [17]. Furthermore, consumers may not be clear about what kinds of data will be collected, how these data will be used and whether they will be shared with third parties. If the financial institutions’ process of data collection and use lacks transparency, in this case, it could potentially infringe on consumers’ privacy rights. Furthermore, data breaches, excessive data collection, and unauthorized data usage also increase the compliance risk of the financial institution [1, 17]. Thus, when using AI credit scoring, relevant institutions should emphasize the authority of the data, data security, and data minimization.

2.3.4 Challenges in Model Risk Management

Static AI scoring models fail to adapt to shifting economic cycles and consumer behaviors, which generates persistent model risk defined as inconsistent prediction performance amid market volatility [18]. Specifically, the AI credit scoring model may operate well with accurate prediction during the period of development and testing, which does not mean that the model will provide the correct results consistently with dynamic societal situations. Consumer behavior, economic conditions and market risks all change over time. If the model is not updated in a timely manner, there may be problems with inaccurate predictions. This becomes obvious when the economy is in a downturn, the unemployment rate is rising, or there are significant changes in consumer behavior. For instance, in the 2008 financial crisis, most of the previously trained models exhibited a deviation in their predictions, and the results were quite inaccurate. Thus, financial institutions cannot rely solely on pre-launch examinations. Rather, it is also necessary to continuously monitor, regularly verify and promptly adjust during the model operation process to ensure the stability of the scoring results [19].

2.3.5 Challenges in Consumer Protection

AI credit scoring poses more challenges in terms of consumer protections. The overlapping risks of algorithm bias, black-box opacity and data privacy leakage jointly form systematic barriers to consumer protection. Consumer protection is highly relevant to the aspects above, including fairness, transparency and explainability, data privacy and model risk management. If the AI credit scor-

ing has biases and inappropriate model risk management, consumers may be wrongly denied loans because the scoring impacts the approval significantly. Meanwhile, due to the application of AI systems, manual review has been reduced, which has already made it more difficult for customers to file complaints. Moreover, if the model lacks interpretability and transparency, it becomes harder for consumers to appeal results due to their limited understanding of the underlying mechanisms. This affects consumers' financial opportunities and may exacerbate the inequality in the credit market [1]. Besides, neglecting the training data for the model can compromise consumers' data privacy, which influences the relationship between financial institutions and customers [17]. Therefore, when financial institutions use AI for credit scoring, they should establish clear explanation mechanisms, complaint channels and manual review mechanisms to protect the basic rights and interests of consumers.

3. Governance Strategy and Feasibility Analysis

Although AI credit scoring improves underwriting efficiency and the ability to identify the risk, it brings problems as mentioned in Section 2, which require financial institutions to establish more systematic governance mechanisms. The goal of governance strategies is not to restrict the use of AI technology, but to reduce the risks associated with algorithmic decision-making while enhancing the efficiency of financial services. This section will discuss how financial institutions establish a responsible governance framework and analyze its technical, economic, and management feasibility. Finally, this article will provide some policy and regulatory suggestions

3.1 Establish a Responsible AI Credit Scoring Governance Framework

Establishing a responsible governance framework for AI credit scoring is an important way to address the risks associated with AI credit scoring. This framework should cover the entire process, including data collection, model development, model application, result interpretation, and subsequent supervision. The measures to establish a responsible AI credit scoring governance framework include strengthening data quality management, improving model interpretability, maintaining the manual review mechanism, establishing a model auditing system and enhancing consumer protection. Only by integrating technology management, risk control and consumer rights protection can AI credit scoring be used more safely, transparently and sustainably in consumer finance [1].

3.1.1 Strengthen Data Quality Management

Standardized full-process data management rules serve as the fundamental solution to mitigate data-driven algorithm bias. The judgment results of the AI model are largely dependent on the quality of the training data and the input data. Thus, financial institutions should do appropriate processing to ensure that the data used to train their AI models is accurate, complete, and recent, which reduces the bias of the model and improves the prediction accuracy of the algorithm. Besides, Clear boundaries should also be set for the use of alternative data. In detail, for sensitive data and alternative data, clear usage boundaries should be established to avoid using data that is unrelated to credit risk or that may cause discrimination [20]. A core data governance principle is data minimization, which requires institutions to only collect the minimal scope of personal information required for credit risk assessment. Excessive collection and long-term storage of irrelevant user data should be prohibited [21]. For financial institutions, only collect data related to credit risk assessment but not those no related data, especially unauthorized sensitive and private data.

3.1.2 Improve Model Interpretability

A set of technical tools and standardized disclosure mechanisms can effectively resolve the black-box limitation of AI credit models. Lots of machine learning models have the feature of the "Black box" problem, which means the related institution cannot always give an appropriate explanation for the result given by the AI algorithm [2]. Because of that, consumers often find it difficult to understand why they were denied a loan, had their credit limit reduced, or had their interest rates increased. Thus, financial institutions should use those models with explainable tools or a high level of transparency in order to explain to consumers and regulatory agencies the main factors that affect credit scores. This transparency requirement does not force institutions to disclose proprietary algorithm codes. Instead, beyond simple approval or rejection notifications, lenders must deliver clear, specific causal factors driving each credit decision.

3.1.3 Maintain the Manual Review Mechanism

Independent manual re-examination acts as a vital error correction channel to offset the defects of fully automated algorithmic judgment. The AI algorithm increases the efficiency of the approval process. However, over-relying on the decision-making by AI models when it comes to loan denials, credit limit reductions, or identifying high-risk customers may increase the risk of errors and unfairness [22]. By implementing the manual review mechanism, financial institutions can re-examine the result provided by the AI model, which ensures the accuracy of the final result. Particularly when consumers file complaints or when automated decisions are disputed, thereby providing

a necessary channel for error correction [23]. To some extent, this will enhance the effectiveness of the appeal process and strengthen the relationship between the institutions and consumers. American Express adopts a typical manual appeal mechanism: applicants whose credit card application are rejected can submit requests for human re-evaluation of their cases. Although this review may not guarantee a change in the outcome, this mechanism provides consumers with an opportunity to explain their circumstances and have their application manually reevaluated [24].

3.1.4 Establish a Model Auditing System

Full-cycle model audit mechanisms realize continuous monitoring and regular calibration of AI scoring models. In order to ensure the model can operate effectively in real consumer finance scenarios, financial institutions should conduct thorough testing before the model is launched to evaluate its accuracy, stability and fairness. Besides, after the model is launched, institutions are also necessary to continuously monitor the performance of the model, checking whether there are any prediction deviations, model drift, or unfair impacts on specific groups. This can help relevant institutions to cope with the impacts on the model caused by the continuous changes in consumer behavior, economic environment and market risks. Furthermore, financial institutions can enhance the objectivity and credibility of model governance by combining internal audits with external independent audits. In detail, for internal audits, the internal audit department of financial institutions can start from the algorithmic procedures of the model to identify the potential flaws that may undermine the fairness of the model's evaluation results [25]. Meanwhile, Financial institutions can hire third-party auditing agencies or focus on customer complaints for auditing purposes, thereby obtaining more objective and comprehensive model testing results [26].

3.1.5 Enhance Consumer Protection

Targeted consumer protection rules guarantee borrowers' basic rights to information, explanation and complaint. Since the credit scoring results directly affect whether consumers can obtain credit cards, consumer loans or BNPL services, financial institutions should ensure consumers' rights to information, explanation and appeal. Specifically, financial institutions should clearly explain to consumers how their data is collected and used. Consumers should be informed of which data will affect their credit scores, such as repayment records, debt levels, income stability, and overdue situations, etc [17]. Meanwhile, when consumers are denied loans or their credit limits are reduced, financial institutions should provide clear and specific reasons, and establish convenient manual review channels. At the same time, in scenarios such as BNPL and online

small loans, financial institutions should also avoid overly stimulating consumers to borrow through algorithms, and prevent consumers from incurring debts beyond their repayment capacity.

3.2 Technical Feasibility Analysis

On the aspect of technology, establishing AI credit scoring governance framework is feasible. Financial institutions can ensure the accuracy of the AI model and reduce model risk through methods such as data cleaning, model testing, interpretability tools and model monitoring. Meanwhile, some technological tools can also assist financial institutions in enhancing model transparency. For instance, explanatory tools can identify the main variables influencing the credit scores [27]. These tools also show which factors have a greater impact on credit scores, such as repayment records, debt levels, and income stability. This will help institutions better understand the model results and also facilitate the explanation of the reasons for credit decisions to consumers. However, it is admitted that challenges exist in technical feasibility. The ability to explain complex machine learning is still limited. Also, the problem of data quality is very difficult to completely eliminate. Therefore, technological governance needs to be combined with manual review, institutional management and regulatory requirements, and cannot rely solely on the AI models and technical tools themselves [22].

3.3 Economic Feasibility Analysis

Regarding the economy, AI credit scoring governance will increase the cost of financial institutions in the short term. Financial institutions need to invest funds in data management, model auditing, system maintenance and manual verification. All of these measures may increase operational costs in the short term and also consume substantial human resources and time. However, in the long term, it is necessary to make these investments. A better governance mechanism can reduce the losses caused by model errors, and lower the compliance risks resulting from algorithmic discrimination, data leakage or opaque decision-making. At the same time, a transparent and fair credit scoring system also helps to enhance consumer trust and maintain the reputation of financial institutions [1]. Thus, although the governance may cause higher operational costs in the short run, it will benefit financial institutions to achieve the goal of sustainable and stable development in the future.

3.4 Management Feasibility Analysis

From the perspective of management, the governance of AI credit scoring requires financial institutions to establish clear internal responsibility divisions and cross-departmental cooperation. AI credit scoring system is not only a

technological tool but also about risk management, legal compliance and protection of consumer rights [5]. Thus, in order to establish a responsible framework, financial institutions should stimulate the collaboration among all department, including data science team, risk control department, compliance department, legal department, customer service department and so on. In detail, the data science team can be responsible for model development and maintenance; the risk control department can assess the credit risks associated with the models; the compliance and legal departments can ensure the models meet regulatory requirements; and the customer service department can handle consumer inquiries and complaints. Through collaboration across different departments, financial institutions can more comprehensively manage the risks arising from AI-based credit scoring. At the same time, financial institutions can found agency particularly for the AI model management, which is responsible for unified management of model development, approval, deployment, monitoring, and updates.

3.5 Policy and Regulatory Recommendations

In terms of policies and regulations, regulatory authorities should strengthen the standardization of AI credit scoring. Firstly, regulators can require financial institutions to enhance the transparency of their algorithms to reduce the possibility of the appearance of the “Black Box” problem [28]. For instance, when consumers are denied loans, their credit limits are reduced, or their interest rates increase, the loan company should provide clear and specific explanations for these actions, rather than merely giving a vague response. Meanwhile, the supervision organization should regulate the use of alternative data. Lenders shall only leverage data closely correlated with credit risk, including repayment track records, debt levels and transaction histories. Meanwhile, regulators should ban the collection of irrelevant sensitive data such as address books, social media posts and real-time geographic locations [9]. Finally, regulatory agencies can require financial institutions to conduct regular model audits to ensure that the AI credit scoring models are accurate, fair and stable. At the same time, regulatory authorities should also act as a third party to regularly assess the accuracy of financial institutions' models, in order to prevent unfair outcomes and protect consumers' rights [25, 26].

4. Conclusion

This study finds that AI credit scoring has fundamentally changed decision-making in consumer finance. Unlike traditional approaches based on manual review, fixed indicators, and static assessment, AI systems can process large and diverse datasets, automate credit approval, and support dynamic risk monitoring throughout the lending

process. In credit card approval, consumer loans, BNPL, dynamic credit limit management, and post-loan monitoring, these systems shift institutions from periodic, experience-based assessment toward real-time, data-driven decision-making. Their value therefore lies not only in greater efficiency, but also in reshaping how consumer credit risk is identified, evaluated, and managed.

The study also finds that the risks of AI credit scoring are closely connected with consumer protection and institutional accountability. Historical or incomplete data may produce algorithmic bias and unfair outcomes for certain groups. Opaque machine learning models may prevent consumers from understanding why applications are rejected or limits are reduced, while extensive data use increases privacy and security risks. These concerns reinforce one another: biased data can generate discriminatory decisions, opaque models can obstruct appeals, and weak data protection can reduce trust. Prediction accuracy alone is therefore insufficient; AI credit scoring must also be evaluated for fairness, explainability, privacy, and accountability.

A responsible governance framework should combine technical, economic, and managerial measures. Financial institutions should strengthen data governance, improve data quality, use interpretability tools, test and monitor models, and retain manual review for disputed or high-risk cases. Although auditing, maintenance, compliance review, and human oversight increase short-term costs, they can reduce long-term losses from model errors, regulatory penalties, and reputational damage. Clear responsibilities, internal audits, complaint procedures, and cross-departmental cooperation are also necessary. Effective governance therefore requires the integration of data governance, explainable AI, human review, model auditing, regulatory compliance, and institutional coordination. These priorities directly address the three research questions presented earlier.

Overall, AI credit scoring can improve the efficiency and risk management capacity of consumer finance, but sustainable adoption depends on balancing innovation with consumer protection. Governance is necessary to ensure that these systems are accurate and efficient as well as fair, transparent, and accountable. Because this study is based on existing literature and publicly available case studies, it does not test real-world consumer finance data, and its findings may not fully represent performance across institutions or markets. Future research should compare traditional and AI-based models using real datasets, particularly in terms of accuracy, fairness, and explainability. It should also compare governance frameworks across countries and examine how regulatory developments influence practical adoption.

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