International Journal of Multidisciplinary Research and Technology
ISSN 2582-7359, Peer Reviewed Journal, Impact Factor 6.325
www.ijmrtjournal.com

IMPACT OF AI-BASED CREDIT SCORING ON LENDING DECISIONS

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Abstract

Through the detailed comparison of the performance of AI-based credit scoring to that of conventional credit evaluation techniques, this study empirically analyses the influence of AI-enabled credit scoring on the decisions of lending. Differences in decision consistency, approval behaviour, and predictive precision are analysed using comparative modelling and a simulated dataset. According to the results, AI-led credit scoring helps to better differentiate risk, boost lending efficiency, as well as allocate credit properly, especially to borrowers with little credit history. The research also highlights significant problems with equity, openness, and governance. Moreover, the data indicate that responsible oversight and implementation are necessary for the long-term integration of AI-driven credit scoring into contemporary lending systems, despite its many advantages.

Keywords: Risk Management, Automated Lending Systems, Financial Inclusion, Algorithmic Decision-Making, FinTech, Credit Risk Assessment, AI-Based Credit Scoring and Lending Decisions.

Introduction

The highly significant lending industry has been found to be presently facing a notable transformation, which is chiefly led by the effective inception regarding artificial intelligence, especially in the processes of decision-making and credit scoring. To be precise, the conventional models for credit assessment, chiefly based on inadequate financial indicators and linear statistical methods, at times fail to properly capture the nonlinear, dynamic and complicated nature regarding borrower behaviour (Tezerjan *et al*. 2021). Therefore, as a consequence of this, financial establishments have started to depend on the systems of credit scoring based on AI, which utilises the framework of automated decisions, alternative sources of data and the algorithm of machine learning in order to improve operational effectiveness and predictive accuracy (Faheem, 2021). Hence, these key systems tend to guarantee faster approval of loans, enhanced management of risk, as well as extended access to relevant credit, especially for thin-file or underserved borrowers.

Figure 1: The Working Process of AI-Driven Credit Scoring

(Source: Bacancytechnology, 2026)

The detailed process through which AI-based credit scoring works has been portrayed in the image above, where user application to final credit score and its possible route has been delineated. On the other hand, the implementation of credit scoring based on artificial intelligence tends to raise key concerns related to accountability, fairness and transparency in core lending decisions. In addition to this, the non-transparent nature regarding most of the models associated with machine learning tends to make the regulatory compliance highly complicated (Siskin *et al.* 2021). In fact, it also opposes the vital explainability requirements, which are definitely imposed by the significant financial regulators. Furthermore, the algorithmic bias, which is identified as embedded in model design or training data, might accidentally strengthen the current socio-economic inequalities. In light of this critical context, it is necessary to empirically investigate the possible ways through which AI-led credit scoring tends to impact the potential lending outcomes in comparison to the traditional approaches (Yadava¸2023).

Therefore, the present research paper explores the influences regarding AI-driven technologies for credit scoring, specifically on key lending decisions through the evaluation of decision consistency, default risk and approval rates in the contemporary financial establishments.

Figure 2: The Application regarding AI-based Credit Scoring

(Source: Bacancytechnology, 2026)

The diagram illustrated above shows the top application associated with Ai-led credit scoring, such as loan approvals, risk management, financial inclusion and credit card insurance, which are further discussed in this study.

Literature Review

The comprehensive literature on credit scoring based on artificial intelligence has rapidly expanded along with the effective digitalisation regarding important financial services, as well as the development of the platforms associated with fintech lending. In this regard, initial research works on efficient credit assessment concentrate on conventional statistical techniques, like discriminant analysis and logistic regression, which primarily depend on the well-organised financial variables, involving earlier payment behaviour, employment history and income (Levy and Baha¸ 2021). To be precise, these models have provided regulatory acceptance and interpretability; however, resources consistently underscored their key limitations in managing complicated borrower profiles and nonlinear relationships, especially in data-rich and heterogeneous environments. In view of the potential advances in the domain of computational power, it has been found that the techniques of machine learning and computational power, like neural networks, support vector machines, random forest and decision trees, have started to be widely adopted in the modelling of credit risk in an effective manner (Teles *et al.* 2021).

In this regard, relevant empirical evidence indicates that these important AI-led models tend to surpass primitive methods in terms of predicting loan performance and default probability. Most importantly, studies that compare the accuracy of the model have regularly reported low-volume misclassification errors and higher values regarding Area Under the Curve for the approach of machine learning, suggesting risk differentiation (Oreški and Oreški, 2018). Therefore, this improves predictive capability, allowing the lenders to properly decrease the credit losses and refine the strategies of pricing, while appropriately maintaining the rates of competitive approval. On the other hand, another significant theme identified during the literary analysis is the acute utilization concerning alternative data within the sphere of AI-powered credit scoring (OMOTOSHO, 2025). It has been noted by contemporary researchers that employing the non-traditional variables like behavioural data, the patterns of mobile usage, digital footprint and transaction histories enable the lenders to examine the borrowers, especially those lacking substantial credit histories.

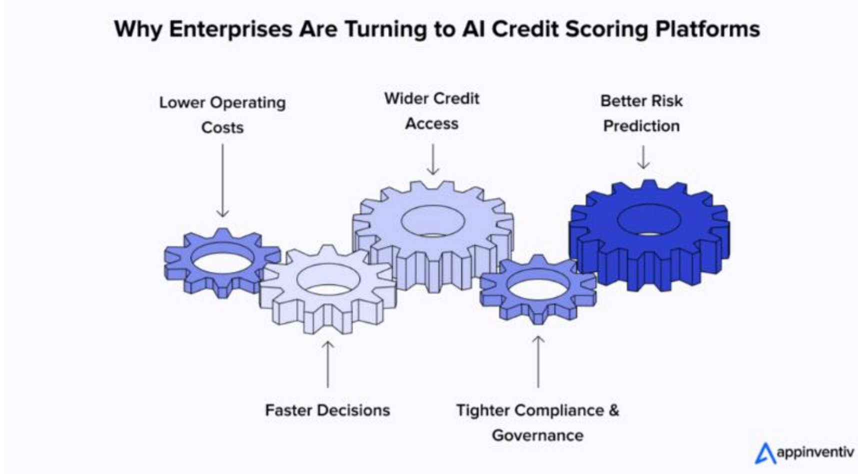

Figure 3: The Reasons for Adopting AI-based Credit Scoring Platform

(Source: Appinventiv, 2025)

The picture outlined above shows better risk prediction, faster decisions, lower operating cost, and wider credit access to be the main reasons for using AI-based platforms for credit scoring. In addition to this, empirical analysis exhibits that suitable alternative data could substantially enhance credit access, specifically for the underserved populations and at the same time, the possibility of default risk is avoided as well. However, it has been cautioned by the present researchers that consent mechanisms, relevance and data quality tend to play a pivotal role in deciding the ethical accessibility and reliability regarding these models (Addy *et al.* 2024). Irrespective of their possible performance advantages, the systems concerning AI-led credit scoring have attracted significant criticism associated with explainability and transparency. To be precise, different models of machine learning tend to operate in the form of black boxes, and this makes it challenging for the lenders to effectively justify the individual decisions regarding lending to the customers and regulators (Lee, 2024). In fact, the literature underlines the rising regulatory burden for explainable AI, especially in the jurisdictions that enforce fair consumer protection and lending laws.

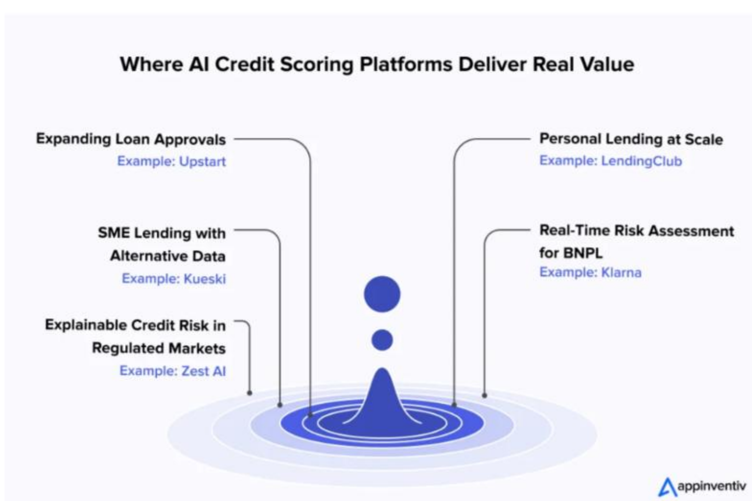

Figure 4: The Areas of Delivering Real Value by AI-based Credit Scoring Platform

(Source: Appinventiv, 2025)

The image illustrated above showcases that real-time risks assessment, explainable credit risk within regulated market, personal lending at scale and expanding loan approvals are are key areas where AI credit scoring offers real value. In this regard, the techniques like the frameworks of interpretable machine learning, regional explanation models and ranking of feature importance are recommended in the form of a partial solution; however, their effect remains debated. On the other hand, algorithmic bias tends to demonstrate another key concern (Trinh and Zhang, 2024). Most importantly, various empirical research has reflected that the training data that are biased in nature could enable the models of AI to generate discriminatory outcomes throughout demographic groups, irrespective of the exclusion of protected attributes from the potential model inputs. It is also argued by the researchers that the historical patterns of lending and proxy variables could ensure that the structural inequalities are unintentionally encoded into the significant automated decisions (Kothandapani¸ 2025). Therefore, the fairness-conscious machine learning, frameworks of ethical governance and the key metrics for bias detection have become key themes in the contemporary research field.

Methodology

The present research has implemented a highly significant empirical research design, integrating comparative analysis and quantitative modelling in order to analyse the potential impacts of AI-powered credit scoring towards vital lending decisions. In addition to this, the methodological approach of this study concentrates on assessing the key differences in terms of the consistency of decisions, accuracy of risk analysis and approval outcomes between traditional and AI-led approaches for credit scoring (Khan *et al.* 2025). In consideration of the limited data related to proprietary lending that is publicly available, the analysis has been undertaken through the usage of a highly simulated dataset, which is calibrated to mirror the lending conditions and characteristics of realistic borrowers, as reported in earlier empirical studies. On the other hand, the significant simulated datasets mainly involve borrower-level observations, especially chosen alternative indicators of data, repayment behaviour, the length of credit history, employment stability and income (Denknalbant *et al.* 2025). Aside from that, two parallel models for credit scoring have been formulated.

The first one, in this regard, tends to demonstrate a conventional approach utilising logistic regression, whereas the second one integrates the model concerning machine learning based on appropriate gradient boosting. Moreover, both models mentioned above have been trained on similar datasets in order to ensure effective comparability, as well as to separate the impact concerning the techniques of modelling on vital lending decisions (Xia *et al.* 2022). On the other hand, the performance of the model has been assessed through the utilisation of standard predictive metrics, which involve the significant Area Under the Receiver Operating Characteristic Curve, recall, precision and accuracy. The lending decisions have been operationalised in the form of binary outcomes, in which loan approval takes place if the evaluated default probability has been found to be below a specific threshold (Aslam *et al.* 2019). The key differences in default outcomes and approval rates throughout models are assessed effectively to measure risk implications and efficiency. In order to investigate the stability of the decisions, a sensitivity assessment has been undertaken by presenting controlled variations within important borrower attributes, as well as by observing the possible changes in terms of approval outcomes.

Analysis

This important section of the research evaluates the possible imperial impacts regarding AI-driven credit scoring, particularly on core lending decisions through the comparison of its decision outcomes and performance with those produced by traditional models for credit assessment. The detailed evaluation concentrates on three important dimensions, which are decision consistency, lending approval behaviour and predictive effectiveness (Kowsar *et al.* 2023). Hence, these significant dimensions together offer key insights into the possible ways through which AI-led systems reshape the practices or credit location within current financial organisations. In this regard, the initial area regarding the assessment concerns predictive efficiency. To be precise, the accuracy of credit scoring tends to hold an area of great prioritisation in the notable lending decisions, because it decides how effectively an individual model tends to differentiate between the key borrowers who will possibly default, as well as those who will not (Sum et al. 2022). Moreover, the comprehensive empirical comparison suggests that AI-led credit scoring showcases consistently robust predictive performance in comparison to the conventional model. Moreover, the algorithm of machine learning has captured appropriate nonlinear interactions, especially among key borrower characteristics, like behavioural indicators, repayment patterns and income volatility, which are at times excluded or simplified in traditional scoring frameworks (Abi, 2025). Hence, as a result of this, it has been identified that the systems based on AI demonstrate enhanced classification concerning borrower risk, decreasing unnecessary rejection concerning creditworthy borrowers and false approvals regarding high-risk applicants.

Dimension	AI-Led Credit Scoring	Conventional Credit Scoring
Risk Differentiation	High	Moderate
Predictive Consistency	Stable	Variable
The Management regarding Nonlinear Patterns	Advanced	Limited
Total Decision Accuracy	High	Moderate

Table 1: The Comparative Performance concerning The Approaches of Credit Scoring

(Source: Self-Created)

The table illustrated above tends to present an accurate comparative summary regarding decision quality and predictive performance between AI-based and traditional scoring models. The key results obtained from the analysis of this table indicate that the credit scoring led by artificial intelligence tends to enhance the possible alignment between genuine lending outcomes and predicted risk. Aside from that, this improved alignment is specifically significant within the competitive lending settings, in which inaccurate risk analysis could result in lost opportunities for revenue generation and maximised default rates. In fact, through the enhancement of decision accuracy, the AI-powered systems tend to support highly effective portfolio management and improved pricing regarding credit risk.

On the other hand, the second important dimension regarding analysis explores the effects of AI-enabled credit scoring on the behaviour of lending approval. In light of a detailed analysis in this regard, it is noted that the decisions on lending are mainly operationalised as rejection or approval outcomes on the basis of properly evaluated borrower risk (Yhip and Alagheband, 2020). Contrary to the traditional systems of scoring, the AI-based frameworks tend to produce highly distinguished approval patterns. Instead of depending on the inflexible thresholds associated with a potentially narrow set regarding financial indicators, the scoring based on artificial intelligence assesses the borrowers comprehensively (Rehman *et al.* 2025). Therefore, this results in an effective redistribution concerning approvals throughout the segments of borrowers, specifically among the applicants having unconventional and limited credit histories.

Moreover, a crucial empirical comparison highlights that the AI-enabled systems help in approving an extensive volume of medium and low-risk borrowers who might be wrongly classified under the conventional models. Simultaneously, the approvals for the applicants who are considered high-risk in nature tend to decline, demonstrating highly precise risk identification. Hence, this transition suggests that the credit scoring with the help of AI does not merely decrease or increase the entire approval rates; rather, it reallocates credit, especially in a highly risk-sensitive way (Swankie and Broby, 2019). These reallocations tend to have significant implications for economic inclusion, because they allow the lenders to expand credit towards the underserved groups and, in this process, the portfolio risks do not increase.

On the other hand, the third important area regarding the assessment concentrates on the stability and consistency of decisions. In this regard, it can be stated that making decisions in a consistent manner is essential for borrower trust, fairness and regulatory adherence (Remolina, 2022). Most significantly, the sensitivity evaluation demonstrates that the long-established models used for credit scoring are highly vulnerable to abrupt changes in decision-making when the attributes of the borrower vary. On the other hand, minor fluctuations in credit or income utilisation could lead to different outcomes of approval, even though the entire risk profile of the borrower remains similar. Therefore, this uncertainty demonstrates the possible linear structure, as well as the inadequate feature instructions regarding traditional models. Contrarily, AI-led credit scoring showcases extensive stability throughout similar profiles of the borrower (Chen, 2025). In fact, through analysing an extended range regarding inputs at the same time, the systems influenced by AI decrease the dependence on a specific variable, and decrease random decision shifts. Hence, this strong stability tends to contribute to highly predictable lending results and decrease the possibility regarding inconsistent treatment concerning comparable applicants.

Aspect	AI-based Scoring	Traditional Scoring
Approval Stability	High	Moderate
Sensitivity Towards Data Noise	Lower	High
Consistency throughout the similar Borrowers	Strong	Variable
Inclusion regarding Thin-File Applicants	Improved	Limited

Table 2: The Comparison Between Decision Stability and Lending Outcomes

(Source: Self-Created)

The table illustrated above tends to summarise the possible variations in decision stability, as well as lending outcomes. Moreover, the findings suggest that with the help of artificial intelligence, credit scoring improves consistency, as well as helps in the maintenance of responsiveness to significant changes associated with borrower risk (Shittu, 2022). On the other hand, extensive stability tends to raise concerns related to excessive dependence on advanced automated systems. However, if the fundamental data distribution tends to change and if systemic biases are present within the important training data, then stable decisions might perpetuate the inaccuracies that are hidden. Hence, this underscores the significance regarding ongoing governance and monitoring.

In light of an operational viewpoint, AI-centred credit scoring impacts the effectiveness of lending. The assessment of risks in an automated manner decreases administrative workload and processing time, allowing reduced operational costs and quicker approval of loans. Moreover, enhanced effectiveness, integrated with improved risk discrimination, reinforces the financial rationale for implementing AI-powered credit scoring (Fonkem, 2025). The empirical assessment has illustrated that the artificial intelligence credit scoring substantially modifies lending decisions through the enhancement of predictive accuracy, stabilising the outcomes of decisions and reallocating the credit approvals in an effective manner.

Discussion

The core findings acquired from this research exhibit that credit scoring powered by artificial intelligence has a multifaceted and substantial influence on the notable lending decisions, expanding beyond enhancements in appropriate predictive accuracy in order to positively impact operational efficiency, decision consistency, and approval behaviour. It has been affirmed by the empirical evaluation that AI-powered models tend to outperform the older methods associated with credit scoring that were used for effectively resolving borrower risks, initially because of their competency to process nonlinear relationships, which are identified among different data inputs (HALLAGI, 2025). Therefore, this crucial ability allows the lenders to make highly informed and data-based decisions, and this also helps in decreasing any default risks. In this way, vital opportunities connected to lending cannot be missed. Aside from that, a highly significant implication concerning the research findings is related to financial inclusion, as well as the allocation of credit.

The technique of credit scoring, modernised by the ecology of artificial intelligence, simplifies a highly nuanced analysis concerning borrowers with non-traditional and linear credit histories, especially through the incorporation of behavioural indicators and alternative data. Therefore, in this way, credit could be expanded to earlier underserved divisions with a rise in the portfolio risk (Raza, 2025). In addition to this, these findings also strengthened the arguments within the current literature by stating that artificial intelligence possesses the possibility to effectively democratize access towards credit, considering that governance mechanisms and data quality are managed in an appropriate manner. Aside from that, the rising stability identified in the lending decisions based on artificial intelligence increases critical considerations specifically for accountability and fairness (Omopariola and Aboaba, 2021). In addition to this, greater consistency decreases arbitrary changes in decisions and enhances the confidence of borrowers; however, it also increases the risks associated with the persistence of biases that might go unnoticed.

Apart from this, if discriminatory practices of lending and historical inequalities are reflected in training data, then the models of artificial intelligence might reproduce these important patterns, especially at scale. Therefore, the findings tend to strengthen the essentiality regarding fairness assessments, monitoring after implementation and bias audits to ensure that the lending outcomes are equitable (Agboola¸2025). Moreover, explainability and transparency have also appeared as potential challenges in this regard. In fact, this technologically advanced credit scoring enhances the standard of decisions. However, its complicated internal logic might limit the ability of the lender to offer transparent justifications to key regulators and notable borrowers (Faheem, 2021). Hence, these critical tensions noticed between interpretability and performance possess regulatory implications, especially in regions with equitable lending requirements and stringent consumer protection. On the other hand, the results reflect that the adoption of artificial intelligence needs to be effectively accompanied by human oversight and explainability tools for the maintenance of trust and adherence.

The application of AI-driven credit scoring transforms the functions of risk managers and credit officers from an organisational standpoint. The decision-making power is increasingly shifting from an individualised judgment, especially towards system-driven suggestions, necessitating relevant skill sets centred on model exception management, governance and validation. This change emphasises the necessity of institutional preparedness and transparent accountability mechanisms to avoid excessive dependency on modern automated systems. The discussion generally suggests that AI-centred credit scoring has significant advantages for inclusion, risk handling, and lending efficiency, but these advantages depend on careful execution (Sanz Martin *et al*. 2025). The efficacy of artificial intelligence in lending relies on ongoing supervision, ethical governance, and regulatory alignment in addition to technological performance. Concerns about clarity and fairness might negate the benefits of credit scoring powered by AI if these safeguards are not in place.

Conclusion

The effects concerning credit scoring using AI on crucial lending decisions were investigated in this study, with an emphasis on decision consistency, approval behaviour, and predictive performance. According to the results, AI-powered models increase the accuracy of risk assessments, improve lending effectiveness, and allow for a more inclusive distribution of credit than conventional scoring techniques. AI-based systems exhibit distinct empirical benefits by reallocating approvals to borrowers with sustainable risk profiles as well as by increasing the consistency of decision results. However, the findings also emphasise the significance of strong governance and continuous monitoring in order to lessen the risks associated with bias and responsibility. As a result, the successful implementation of sustainable and ethical AI in lending is dependent upon its effective implementation.

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Use for Citation: Sanya Gupta. (2026). IMPACT OF AI-BASED CREDIT SCORING ON LENDING DECISIONS. International Journal of Multidisciplinary Research and Technology, 7(1), 24–32. https://doi.org/10.5281/zenodo.18386727