Influence of Artificial Intelligence on The Efficiency and Accuracy of Credit Scoring in Digital Lending in Kenya

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Abstract
Kenya's financial services sector has rapidly evolved, with digital lending playing a crucial role in fostering economic growth and financial inclusion. However, despite the ease of access to financing through digital lending, the sector has faced many challenges, including rising default rates, unorthodox loan collection methods, limited borrower information to minimize *repayment risks*, *credit risk*, *fraud*, and *operational inefficiencies*. Drawing on Diffusion of Innovation (DoI) theory, this study examines how artificial intelligence affects the efficiency and accuracy of credit scoring in digital lending in Kenya. Specifically, it will assess the accuracy and effectiveness of AI in credit scoring, its efficiency in processing credit/loans, and its role in improving customer and institutional outcomes. Using a descriptive research design, a mixed-methods approach incorporating structured surveys and interviews will gather data from Kenya's 32 regulated digital lenders. The data will cover the period from when each firm adopted AI technology up to 2025. The study will test validity and reliability using content validity and Cronbach's alpha. This study aims to provide insights into how AI-powered digital lending can be leveraged to reach and include the unbanked population. Similarly, the solutions generated aim to maximize AI's effectiveness and relevance within Kenya's socio-economic and cultural context.

Keywords: Artificial intelligence, credit scoring, digital lending, efficiency, effectiveness

Introduction

Kenya's financial services sector has evolved rapidly, with digital lending playing a crucial role in fostering economic growth and financial inclusion. This exercise began in 2012, after Safaricom launched M-Shwari. Since then, the number of digital lenders and loans disbursed has grown substantially. By October 2023, the Central Bank of Kenya (CBK) had regulated 32 digital lenders, yet about 400 applications were seeking regulation (KIPPRA, 2023).

However, despite the ease of access to financing through digital lending, the sector has faced many challenges, including increased default rates resulting in negative listings by the Credit Reference Bureau (CRB), aggressive collection of loans using unorthodox means (KIPPRA, 2023), and limited information about the borrower's characteristics to minimize repayment risks, credit risk, fraud, and operational inefficiencies (FSD, 2019).

Defined as the simulation of human intelligence processes by machines, especially computer systems (Laskowski, 2023), Artificial Intelligence (AI) refers to the science of making machines that can think like humans while processing substantial amounts of data in diverse ways, unlike humans. AI includes machine learning (ML), AI-powered automation tools, and natural language processing (NLP) (Lopez, 2024). The goal of including them in any process is to help them recognize patterns, make decisions, and judge like humans (Pattam, 2021).

Given the challenges facing digital lenders, Addy et al. (2024) observed that AI in credit scoring offers significant benefits for financial inclusion and risk management. However, they also emphasize the need to address ethical concerns and potential biases. As such, they recommend further research into the long-term impacts of AI in credit scoring, the scalability of AI models, and their applicability across various financial contexts. Building on these insights, this study aims to examine the role of AI in credit scoring, with a focus on its accuracy and efficiency in the digital lending sector in Kenya.

Caire and Kossman (2003) defined credit scoring as a scientific method of assessing the credit risk associated with new credit applications. Regarding the efficiency and accuracy of credit scoring in digital lending, AI has been used to analyse past (historical) clients' and business data to identify trends, better understand (potential) clients, and predict future events such as credit repayment (Vidal & Barbon, 2019). This efficiency describes minimizing material inputs to maximize economic outputs (van Ewijk, 2018). Therefore, once AI is adopted for efficiency purposes, businesses benefit from cost savings; the ability to identify and capitalize on new opportunities improves; better customer-focused service; quick processing of many applications, minimizing the costs associated with manual credit evaluation and optimizing resource utilization in order to obtain better overall performance and reduced wastages (Vidal & Barbon, 2019). However, accuracy refers to the ability to correctly predict a borrower's likelihood of repaying a loan. When used appropriately, the credit scoring system then classifies borrowers as either low-risk or high-risk based on their creditworthiness (Caire & Kossman, 2003).

As observed by De Cnudde et al. (2019), credit score information comes from socio-demographic data on gender, age, civil status, business experience, time at the current residence, and type of residence; the number of days a client is delinquent; personal credit history with other financial institutions or utility companies; psychometric data, which assesses a person's knowledge, abilities, attitudes, and personality traits; and big data, which includes information from phone companies, utilities, retailers, or social networks (Facebook, Twitter, LinkedIn, Yahoo!).

Accordingly, this paper examined how Artificial Intelligence influences the efficiency and accuracy of credit scoring in Kenya's digital lending sector. Specifically, it assessed credit scoring accuracy, AI effectiveness, efficiency in processing credit and loans, and its role in improving customer and institutional outcomes.

This study adopted the Diffusion of Innovation (DoI) Theory introduced by Rogers and Williams (1983). However, the theory was significantly updated in 2003. This theory explains how new ideas and technologies spread within society. It highlights five factors that influence why people or organizations adopt innovations. These factors include: its benefits, how well it fits with existing practices, how easy it is to use, whether it can be tested, and how visible its results are. The theory also describes five stages that people go through in deciding to adopt something new. These stages are: learning about it, being persuaded, making a decision, putting it into use, and confirming that choice. Researchers have applied this theory in agriculture, marketing, public health, and technology. This study focuses on technology implementation, specifically on how AI-driven solutions like machine learning affect credit scoring and fraud detection within Kenya's digital lending sector, where trust and familiarity remain major challenges.

Literature Review

Scoring refers to a method of assigning a numerical value (the 'score') to a client in order to predict how he or she is likely to behave relative to others in terms of some action in the future. By analysing a sample of past (historical) client and business data, trends are deduced to better understand (potential) clients and predict future events such as credit repayment (Vidal & Barbon, 2019). Credit scoring is a scientific method of assessing the credit risk associated with

new credit applications. It uses quantitative measures of the performance and characteristics of past loans to predict the future performance of loans with similar characteristics (Caire & Kossman, 2003).

Through credit scores, financial institutions can use scoring models to assess a borrower's credit risk and support credit evaluation. These scores assess a person's creditworthiness, or the likelihood they will repay a loan. Furthermore, credit scoring is the cornerstone of the financial industry, influencing access to loans, mortgages, credit cards, and various financial services (Bhat et al., 2023). Information necessary in credit scores comes from socio-demographic data such as gender, age, civil status, business experience, time residing at current residence, type of residence; behavioural data which may include number of days a client is delinquent; Credit Reference Bureau (CRB) data which includes personal credit history with other financial institutions or utility companies; Psychometric data which determines a person's knowledge, abilities, attitudes, and personality traits; and lastly, big data which includes information from phone companies, utilities, retailers or social networks (Facebook, Twitter, LinkedIn, Yahoo!) (De Cnudde, et al., 2019).

Credit scoring models are not intended to replace loan officers and other commercial staff but to complement and facilitate their work by supporting the assessment of willingness to pay (ACCION, 2016). Similarly, credit scoring cannot predict individual loan losses; rather, it predicts the likelihood or odds of a 'bad' outcome (Caire & Kossman, 2003).

According to Palmer and Torgerson (1999), efficiency is concerned with the relationship between resource input costs (labour, capital, or equipment) and their intermediate outputs. Resource efficiency describes minimizing material inputs to maximize economic outputs (van Ewijk, 2018). In credit scoring, efficiency refers to how effectively the system processes applications and makes credit decisions. When an organization first uses data, it can be complicated and time-consuming. Once adopted, however, significant improvements in business efficiency and cost savings occur; the ability to identify and capitalize on new opportunities improves; there is better, customer-focused service; quick Processing of many applications, minimizing the costs associated with manual credit evaluation and optimizing resource utilization in order to obtain better overall performance and reduced wastages (Vidal & Barbon, 2019).

Accuracy refers to how close an instrument's reading is to the true value when measuring a signal or other physical quantity (Arbiter Systems, 2024). In credit scoring, accuracy refers to the scoring system's ability to correctly predict the likelihood that a borrower will repay a loan. In this, the credit scoring system classifies borrowers into either low-risk or high-risk based on their creditworthiness; minimizes errors by reducing both false positives (approving loans to high-risk borrowers) and false negatives (rejecting loans to low-risk borrowers); and accurately predicts defaults and improves loan portfolio performance/health (Caire & Kossman, 2003).

Salter (2023) explained the use of Artificial Intelligence and its Applications in Behavioural Credit Scoring, noting that adoption of machine learning methods remains minimal in financial risk management. Therefore, as deep learning methods have been evaluated for behavioural credit scoring based on performance, research has not holistically evaluated these models on both performance and explainability. In conclusion, given the strict regulatory environment, banks have been hesitant to implement machine learning or deep learning models, especially those that lack sufficient explainability to meet regulatory requirements. To confirm this, this study examines whether digital lending companies in Kenya implement regulatory frameworks that recognize the transparency and explainability of traditional credit scoring methods.

Addy et al. (2024), in their comprehensive review of AI models and predictive analytics in credit scoring, examined the historical context, the transformation of traditional credit assessment methodologies, various AI models used, and the real-world implications of AI in

credit scoring. They aimed to explore AI's transformative impact on credit scoring, highlight the strengths and limitations of different AI models, examine the integration of alternative data sources, discuss the role of explainable AI, and address the ethical considerations associated with AI models in credit scoring. To achieve these objectives, the authors synthesized existing literature on AI in credit scoring. In particular, they examined various AI models and evaluated their effectiveness, scalability, and interpretability. Ultimately, Addy et al. (2004) concluded that AI has significantly improved credit scoring accuracy and efficiency. However, the authors also observed that AI in credit scoring has positive implications for financial inclusion and risk management but requires careful attention to ethical considerations and potential biases. Although the results were remarkable, the study also noted the need for further research on the long-term impact of AI in credit scoring, the scalability of AI models, and their applicability across different financial contexts. Building on this, this study examines the AI perspective in Kenya's digital lending sector.

Tyagi (2022) analysed machine learning models for credit scoring with explainable AI and optimizing investment decisions in the USA. Because of regulatory requirements and the need for trust in automated decision-making in financial services, the study aimed to improve the transparency and predictive power of machine learning models used for credit scoring by employing explainable AI techniques such as SHAP (Shapley Additive Explanations) and LIME (Locally Interpretable Model-Agnostic Explanations). Using data from the Lending Club website for 2016, the author analysed about 110,000 records using logistic regression; the results showed that explainable AI techniques like SHAP and LIME improved the transparency of complex machine learning models. In conclusion, the author observed that explainable AI can significantly enhance the transparency and trustworthiness of machine learning models used in credit scoring. As an area for further study, Tyagi (2022) recommended incorporating more diverse data sources and testing the models in different financial contexts to validate their robustness and generalizability. Accordingly, this study will compile information from diverse sources and conduct an analysis to assess the robustness and generalizability of AI use within digital lenders in Kenya.

Grennepois and Robin (2019) studied artificial intelligence (AI) and machine learning for credit risk management in France. They explored methods to improve model accuracy and explainability. The study aimed to improve the predictive power and explainability of credit risk models while addressing the trade-off between accuracy and transparency in AI applications. It used Shapley value analysis and a hybrid approach combining logistic regression with machine learning models such as Random Forest and Neural Networks. The results show that credit amount, borrower age, and loan duration significantly affect credit scores. In conclusion, the authors observed that model explainability and transparency are crucial for quantifying model risk, as financial institutions can better manage and stress-test models by understanding their sensitivity to variables. As a recommendation, financial institutions should use hybrid approaches that combine traditional and advanced AI models to balance accuracy and interpretability. Although this study used Shapley value analysis, it is computationally intensive, especially with a large number of features, observations, and complex models.

Schmitt and Roper (2023) conducted a study on artificial intelligence (AI)-enabled credit scoring in banking and FinTech in order to unearth the maximum prediction accuracy in the UK. Their objective was to improve the prediction accuracy in credit risk assessment among financial institutions. Such a study was critical to mitigate potential financial losses from defaults, enhance competitive positioning, and strengthen overall financial stability. Their study employed Logistic Regression, Random Forest, Gradient Boosting, and Deep Learning. The dataset included real-world credit-risk data for training and evaluation. The results show that machine learning performance depends on the underlying dataset. Similarly, combining the base models into a super learner improved prediction accuracy across all datasets. In

conclusion, super learning effectively enhances the performance of individual AI/ML models in credit scoring. As a recommendation for further studies, Schmitt and Roper (2023) observed that integrating unstructured data, such as social media activity or transactional text data, should enhance prediction accuracy. Similarly, they recommended incorporating bias and fairness considerations in credit scoring models to ensure equitable lending practices. To advance these recommendations, this study will investigate the relationship between social media, transactional text, and AI prediction accuracy.

Khemakhem and Boujelbene (2017) evaluated the effectiveness of artificial neural networks (ANN) and support vector machines (SVM) for credit risk assessment in Tunisia and compared them with traditional statistical methods. Using data from 408 borrowers, they found that ANN outperformed both SVM and traditional methods in accuracy (90.2%) and in reducing type I errors. They concluded that AI, especially ANN, offers a more reliable alternative for credit scoring and recommended that financial institutions adopt it. However, the study's findings were limited by its focus on a single Tunisian bank. In contrast, the current study aims to include all registered digital lenders in Kenya to enhance the generalizability and relevance of its findings on AI's impact on financial stability.

Moscato and Sperlì (2023) developed benchmark machine learning models for credit scoring using data from the Lending Club social lending platform. Their study aimed to improve creditworthiness predictions by addressing data imbalance and applying Explainable AI (XAI) tools for model interpretability. Using 877,956 samples and 151 features, they applied various sampling strategies and found that the Random Forest model with random under-sampling yielded strong AUC and specificity despite lower accuracy. They concluded that their approach effectively improved credit-scoring predictions and recommended further research on sampling techniques and XAI to enhance model trustworthiness and interpretability.

Sadok et al. (2022) examined AI's role in transforming credit scoring and risk assessment in the U.S. mortgage market. Their study highlighted AI's potential to enhance decision-making through big data while also addressing its socio-economic implications, particularly issues of bias, opacity, and ethical concerns. They concluded that although AI can improve credit risk assessment and promote financial inclusion, it also poses significant legal and ethical risks. The authors emphasized the need for transparency, accountability, and regulatory oversight to mitigate these challenges. Building on this, the current study will empirically assess AI's benefits in credit scoring and examine regulatory compliance among digital lenders in Kenya.

Gambacorta et al. (2024) studied the impact of machine learning and non-traditional data on credit scoring and the effectiveness of these models in predicting borrower defaults and losses in China. Their study compared the predictive power of machine learning and non-traditional data-based credit scoring models with traditional credit scoring models, especially during periods of economic shock. They used descriptive statistics and quantile regression to compare models during normal times and an exogenous regulatory shock. Using 343,976 observations across variables including default dummy, loss rate, fintech credit score, and other financial and demographic metrics, the results showed that machine learning models based on non-traditional data outperformed traditional models in predicting losses and defaults, particularly after a regulatory shock. They concluded that machine learning models using non-traditional data are more effective in credit scoring, especially in volatile economic conditions. As a recommendation, they argued that there is a need for financial institutions to incorporate machine learning techniques into their credit scoring processes, an aspect this study investigated.

Theuri and Olukuru (2022) examined AI implementation in banking, particularly through a dashboard that aggregates key financial data and insights for decision-makers in Kenya. The study explored how AI and machine learning (ML) applications are transforming the banking industry by enhancing decision-making and improving operational efficiency. Using anonymized financial data (1,056,320 transaction records and 5,369 client records) from a

Czech bank, the authors used Microsoft Power BI for data visualization and analysis. The results showed that AI provided real-time insights through dynamic dashboards, enhancing decision-making in banks. Based on these results, the authors concluded that AI significantly improves the banking sector's ability to analyse data, forecast trends, and make informed decisions, ultimately leading to better customer service and risk management. As a recommendation, there is a need for banks to invest in the necessary infrastructure to support AI and ML applications effectively. Similarly, banks need to build data science and engineering skills and knowledge to support AI applications in banking. Given the challenges in the real-world application of these models due to the need for specialized software and hardware, this study will investigate the level of investment devoted to supporting AI within digital lenders in Kenya.

Akello (2022) outlined AI applications across sectors, the challenges faced, the risks to human rights, and recommendations to mitigate these risks. The study aimed to explore AI's impact on human rights and identify the challenges and risks associated with AI adoption in Kenya. Through a literature review, an analysis of AI applications in key sectors, and an assessment of the regulatory framework on data protection and AI ethics, the findings revealed that AI systems require large datasets, including personal and sensitive data, to function effectively. Similarly, restricting access to data creates significant risks of bias and discrimination in AI outputs. Lastly, although compliance with the Data Protection Act is crucial, it may hinder innovation if not balanced properly. In conclusion, this policy brief indicates that adopting AI in Kenya presents both opportunities and challenges, particularly regarding human rights and ethical considerations. Similarly, there is a need for clear guidelines and frameworks to ensure responsible AI use. As a recommendation, there is need for the government to implement measures to protect human rights while fostering AI innovation; the workforce should have its capacity built to effectively utilize AI technologies as well as the need to establish clear regulatory frameworks to guide the ethical use of AI and data protection. Although this study explored AI use and its potential risks to human rights, it will now examine its use among digital lenders.

Ampountolas et al. (2021) studied the application of machine learning techniques to improve credit scoring in micro-finance institutions (MFIs) in Africa. To evaluate the effectiveness of machine learning models in assessing defaults in micro-credit lending, especially in the absence of centralized credit databases, the authors used various machine learning algorithms to analyse data and predict defaults. The trials found that machine learning algorithms effectively extracted hidden information from datasets, helping assess defaults in micro-credit. Based on these results, they concluded that machine learning techniques can significantly enhance credit scoring in microfinance, providing a viable alternative to traditional methods that rely on historical credit data. Given this, Ampountolas et al. (2021) recommended further exploring machine learning methods in financial contexts, particularly for institutions serving unbanked populations. They also suggested improving data collection practices to enhance model training. Following this recommendation, this study focused on fintech lenders that primarily advance credit to unbanked populations.

Kshetri (2021) investigated the role of AI in promoting financial inclusion, addressing regulatory compliance, fraud reduction, risk assessment, and improving collection processes within the developing countries of Malaysia, Chile, and Indonesia. The study aimed to explore how AI can enhance financial inclusion for unbanked populations in developing countries and to identify the challenges and opportunities of implementing it. Using qualitative analysis of existing AI applications in financial services, along with case studies and examples from various FinTech companies, the results indicated that AI tools can help financial institutions comply with regulations, reduce fraud, and assess lending risks effectively. Hence, the researcher concluded that while AI has the potential to significantly improve financial inclusion, its current application in developing countries remains in the early stages, with many

projects still at the prototyping level. As a recommendation, it is imperative to invest in AI talent development and training for financial institution staff; encourage regulatory frameworks that support AI adoption while addressing privacy and employment concerns; there is need for continued research and development of AI applications tailored to the specific needs of developing markets. Although Kshetri (2021) focused on Malaysia, Chile, and Indonesia, this study focused on Kenya, a developing African nation.

Methodology

This paper adopted a descriptive research design and opted for a mixed-method approach, which incorporated a structured surveys and interviews. A census approach was adopted. However, data were gathered from 30 of Kenya's 32 regulated digital lenders. This represented a 94 percent response rate. Similarly, Cronbach's alpha of 0.709 (Appendix 2) also indicated that the information was reliable. The results in the graphs below provide insights across three thematic areas: (1) credit scoring accuracy and effectiveness, (2) processing efficiency, and (3) customer and institutional outcomes. The descriptive data analysis in this study helped organize raw data into meaningful information using averages, frequencies, and percentages. This helps technical and non-technical audiences interpret the results easily. Similarly, the easy-to-understand results lay a groundwork for deeper statistical analysis.

Effect of AI on Credit Scoring Accuracy and Effectiveness

This objective was undertaken to assess respondents' perceptions of how AI could improve credit scoring accuracy and effectiveness, especially in loan repayment and loan defaults. Figure 1 contains the results.

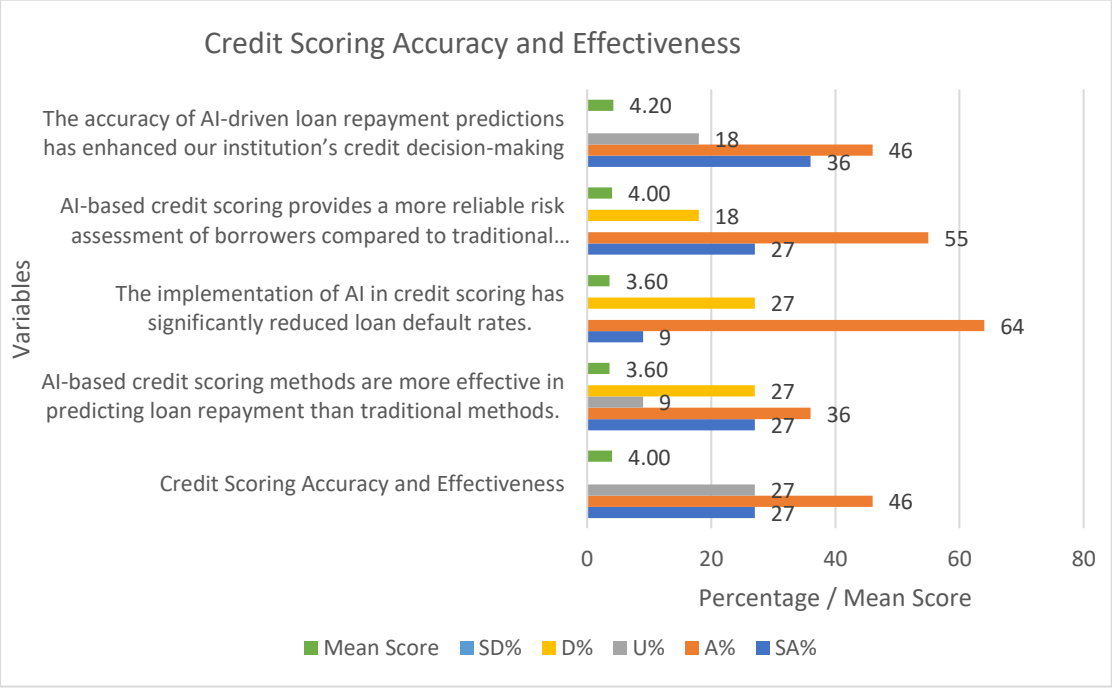


Fig.1: Effect of AI on Credit Scoring Accuracy and Effectiveness

Regarding credit scoring accuracy and effectiveness, most respondents expressed strong confidence in AI's role in improving lending decisions. Specifically, 82 percent of participants, with a mean of 4.2, agreed or strongly agreed that AI-based credit scoring improves credit decision-making. Similarly, a high proportion (82%) endorsed the view that AI provides a more reliable assessment of borrower risk compared to traditional methods (mean = 4.0). Sixty-three percent of the respondents (with a mean of 4.0) believed that AI is more effective than

conventional techniques. Overall, 73 percent (with a mean of 4.0) agreed that AI enhances the overall accuracy and effectiveness of credit scoring. These results are in consonance with Bhat et al. (2023) and Addy et al. (2024), who also recognized the significance of AI in enhancing the accuracy and efficiency of credit scoring. However, when asked whether AI has led to a reduction in loan default rates, the level of agreement declined. Only 73 percent supported this statement, and the item recorded the lowest mean score (3.6), suggesting a perceived gap between AI's predictive capabilities and its influence on borrower repayment behaviour. This finding also corroborates Caire and Kossman (2003), who asserted that AI's use in Credit scoring cannot predict individual loan loss.

The analysis in Table 1 also indicated that Credit Scoring Accuracy and Effectiveness had a perfectly symmetrical distribution (Skew =0) with fewer extreme values, suggesting that its tail was flatter than normal (Kurtosis= -1.111). Hence, it was noted that the predictive precision of AI alone is not enough to cause a behavioural change among borrowers.

Table 1: Descriptive Statistics

	CSAE	PE	CIO
Mean	4	4.36	4
Skewness	0	0.661	-1.578
Kurtosis	-1.111	-1.964	5

Effect of AI on Processing Efficiency

This objective gauged respondents' perception of AI's processing efficiency in loan approvals and loan applications. Results are as per Figure 2.

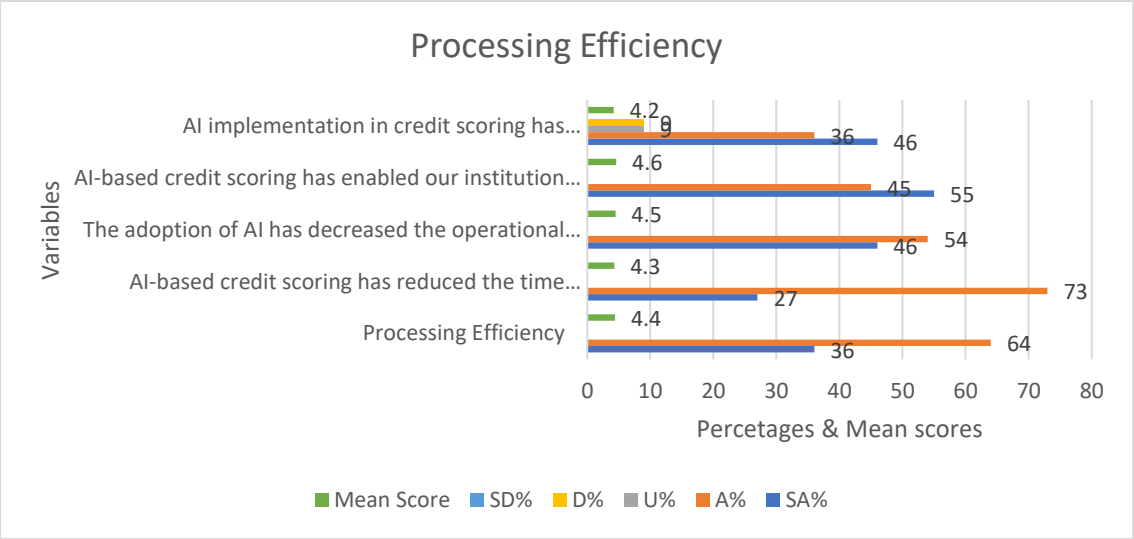


Fig.2: Effect of AI on Processing Efficiency

Based on AI's effectiveness on processing efficiency, respondents showed an overwhelmingly positive consensus. One hundred percent of respondents either agreed or strongly agreed that AI enables processing a higher volume of loans daily, reduces the cost per loan application, and shortens loan processing time, with mean scores of 4.6, 4.5, and 4.3, respectively. This aligns with Vidal and Barbon (2019), who also noted that AI speeds up the processing of many applications. Additionally, 82 percent acknowledged AI's ability to streamline the loan approval process (mean = 4.2).

These results emphasize the value of AI in optimizing internal workflows, reducing human error, and enhancing turnaround times. These are critical success factors in the competitive digital lending environment; thus, this view aligns with Addy et al. (2024), who also found that AI enhances efficiency. Overall, the results indicated that through AI adoption, there has been a significant efficiency in operations, especially in quick loan processing and reduced costs.

Customer and Institutional Outcomes

To assess AI's role in supporting customer and institutional outcomes, such as risk weighting, transparency, customer satisfaction, and fairness and bias, Figure 3 outlines the results.

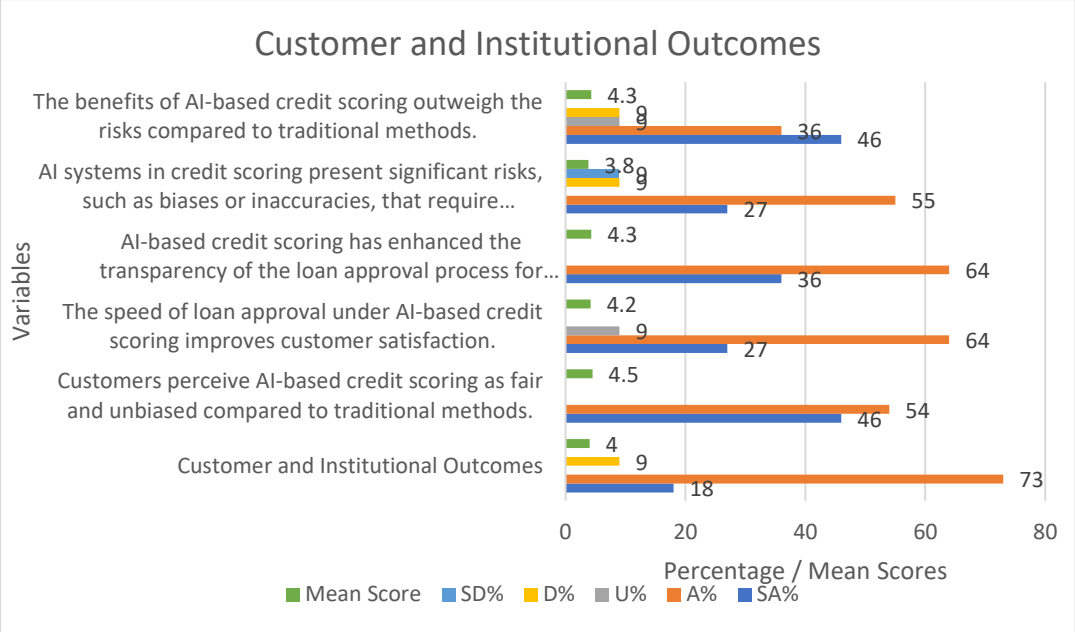


Fig. 3: Effect of AI on Customer and Institutional Outcomes

On customer and institutional outcomes, most respondents recognized AI's benefits from both service delivery and risk management perspectives. A substantial majority (90%) agreed that AI improves customer satisfaction due to faster loan processing (mean = 4.3). Similarly, 80 percent acknowledged that AI systems carry risks such as algorithmic bias and inaccuracies that require deliberate management (mean = 4.3). This result aligns with Addy et al. (2024), who also emphasized the need to address ethical concerns and potential biases in AI use in credit scoring. Interestingly, 82 percent also believed that AI's overall benefits outweigh its risks (mean = 4.3), indicating a cautiously optimistic stance among employees.

Transparency in loan approval processes was another area where AI was viewed favourably, with 100 percent of respondents agreeing that AI enhances transparency (mean = 4.2). This result aligns with Tyagi's (2022) finding that AI can significantly enhance the transparency and trustworthiness of machine learning models used in credit scoring. However, while respondents were positive about AI's fairness, the statement on whether customers perceive AI-based decisions as fairer than traditional methods received a relatively lower mean score of 4.0. This suggests that while employees recognize AI's potential for fairness, lingering concerns about customer trust and understanding of AI-driven processes undermine Tyagi's (2022) claim that AI enhances transparency. With 80 percent acknowledging risks like algorithmic bias alongside high satisfaction, this contradiction suggests respondents recognize bias but still strongly support AI adoption. As a result, respondents underweight the risks relative to perceived efficiency gains.

Conclusion and Recommendation

In conclusion, respondents strongly believe AI-based credit scoring is effective, efficient, and beneficial, though they have slightly less confidence in its direct impact on reducing loan default rates. Additionally, there is an acknowledgment of potential risks like bias and inaccuracy regarding the use of AI; hence, the need for its further development and careful management.

As a recommendation, digital lending institutions should continue adopting and integrating AI-based credit scoring systems to improve efficiency and decision-making. However, to address concerns about bias, inaccuracy, and limited impact on loan default reduction, there should be a continuous improvement of AI systems by regularly evaluating the different models in the market and including diverse data inputs, especially psychometric data, to assess an individual's honesty and reliability. The model should also include a social credibility score (association with those with good repayment records). Furthermore, institutions should establish clear ethical guidelines and regulatory compliance frameworks to ensure responsible and transparent use of AI in credit scoring.

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