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The Role of AI in Improving Credit Scoring Models for Better Lending Using the TOPSIS Method

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ABSTRACT

One of the most important aspects of risk management for financial institutions is assessing credit risk. Credit scoring models are important tools for evaluating loan applications because they provide a systematic way to assess creditworthiness. While traditional statistical models have been widely used, artificial intelligence (AI) has emerged as a more efficient alternative due to its ability to process large datasets and improve predictive accuracy. The growing reliance on AI-powered models has transformed lending practices, improving decision-making, reducing default risks, and enhancing financial stability. The focus of this research is on exploring AI-based credit scoring models and their impact on financial institutions. Traditional credit scoring methods often lack accuracy and efficiency, leading to increased risks and losses.

AI methods like machine learning and deep learning offer a more reliable method, analyzing huge amounts of data and spot patterns that people are not aware of. Gaining insight into how AI affects credit scoring helps with risk management, loan selection, and financial inclusion. Other options for A1, A2, A3, A4, and A5. Income level, credit score, existing debt, and recent credit inquiries are all part of the assessment. The results showed that A3 ranked lowest and A4 ranked best. A1 has the highest value for The Role of AI in Enhancing Credit Scoring Models for Better Lending according to the TOPSIS Method approach.

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Introduction

One of the most important components of risk management for financial institutions is assessing credit risk. The probability of default is similar to entropy, a probability-based measure of uncertainty, and credit rating models are an important tool for assessing credit. More accurate classification models are essential to improving risk assessment. Artificial intelligence (AI) models are becoming increasingly popular due to their high accuracy and ability to effectively analyze various types of data, whereas statistical models have historically been the go-to option. Continuous advances in AI techniques, particularly in the field of risk assessment, have further contributed to their growing adoption. [1] Credit scoring models are often used by financial institutions to determine whether loan applicants are low-risk borrowers. These models offer several benefits, including reducing the costs associated with credit analysis, speeding up the loan approval process, ensuring effective loan recovery, and minimizing potential financial risks. [2] The Recent global financial crisis has drawn unprecedented attention to the credit risk faced by financial institutions.

An effective credit risk assessment system helps financial institutions provide loans to qualified applicants, maximize profits, reject unqualified borrowers, and minimize potential losses. In recent years, credit assessment systems have become an important tool for assessing credit risk, improving liquidity, reducing financial risks, and supporting management decisions. For businesses to be profitable and financially stable, these estimates must be accurate. [3] The credit business has expanded significantly over the past 20 years, with significant growth in credit card lending, auto financing, single-family mortgages, and installment loans. During this period, financial institutions have extensively used credit scoring methods to improve cash flow management and expedite debt collection processes. The many benefits of credit scoring include lower credit investigation

costs, faster loan approval, better debt collection efforts, and improved account monitoring. [4] First, by eliminating redundant variables, the genetic algorithm reduces the number of attributes, improving the performance and interpretation of the decision tree. Meanwhile, noisy data is filtered using the clustering technique.

According to computational findings, the prediction accuracy of credit scoring models, such as decision trees, neural networks, support vector machines, and random subspace classifiers, has been significantly improved by combining evolutionary methods with K-means clustering. [5] Initially, credit scoring was determined through subjective assessments based on personal judgment. Later, it evolved into a rating framework using the 5Cs: character, capital, collateral, capacity, and economic conditions. However, as the number of applicants increased significantly, manual scoring became impractical. To address this challenge, two automated credit scoring approaches were developed: Artificial Intelligence (AI) approaches and statistical methods. [6] Largely due to data collection challenges, quantitative credit scoring models for commercial loans were developed significantly later than models for consumer loans. In many countries, legal restrictions such as privacy laws and other factors have prevented the establishment of publicly accessible databases.

As a result, financial institutions have been forced to rely solely on their internal data. However, in recent years, some data has become publicly available across different countries and financial institutions, allowing researchers to develop a variety of quantitative credit scoring techniques. [7] Many developing countries, especially those with heavily privatized economies, rely heavily on the banking sector for their economic and social well-being. Banks provide financial support through loans to industries such as manufacturing, agriculture, trade, and services. These sectors, in turn, create employment opportunities, which increase purchasing power, consumption, and savings. Therefore, it is crucial to make the right credit decisions and ensure an efficient and successful decision-making process. [8] While credit scoring techniques are widely adopted by lenders and demonstrate their value, there is limited solid evidence on how these benefits are realized, their overall impact, and their implications for financial institutions.

A more focused approach that includes detailed applicant and credit-level data would help identify the specific mechanisms by which credit origination and credit outcomes are affected, as well as the magnitude of these effects. [9] Scoring models are used by intermediary platforms to control risk, protect investors, and maintain financial stability. Based on risk levels that affect investor returns, these models rate loan applicants and, in some cases, set variable interest rates. Models that use scoring approaches to predict or analyze competitor returns in the peer-to-peer (P2P) lending industry show similar patterns. In machine learning frameworks, intermediary factors are typically only taken into account through feature importance analysis, although they are implicit in classic econometric models that use regression. [10] The US subprime mortgage crisis and the European sovereign debt crisis resulted in significant financial losses for major companies in the US and Europe. These events drew attention to the increasing need to manage credit risk and sparked a debate about the use of credit default swaps (CDS).

As a result, the field has attracted increasing interest from scholars and industry players. Financial institutions have made it a top priority to develop accurate credit scoring models to control credit risk exposure and increase profitability. These models have been improved using various machine learning and statistical approaches. [11] Credit rating challenges are typically combined with classification using statistical techniques. Identifying advanced classifiers that match the characteristics of data samples is essential to achieve accurate and reliable results tailored to specific credit rating applications. The development of classification techniques has progressed from basic parametric methods to more sophisticated non-parametric statistical approaches. Initially, a class-based classification method was introduced to refine the model classification into more uniform clusters, which helps to create a more effective ensemble classifier for credit rating models. [12] For banks and other financial institutions, credit scoring models are essential, especially in various real-world applications. In deciding whether to approve or deny a loan application, banks typically use credit scoring models and judgment-based methods.

The purpose of this paper is to investigate the use of data mining techniques in credit scoring models for determining creditworthiness. In addition, it examines how these models can predict events such as payment defaults, enabling early intervention to reduce financial losses. [13] An artificial intelligence method called neural networks (NN) uses interconnected neurons to process information simultaneously, in order to mimic how the human brain works. Input, hidden, and output layers make up their structure. In the input layer of loan assessment applications, the NN model first collects the characteristics of an applicant. Following processing, the hidden layer retrieves these characteristics for further analysis. After receiving the calculated numbers, the output layer finally decides whether to approve or deny the loan. [14] As the lending industry has expanded and loan portfolio management has become increasingly complex, credit scoring models have become essential for assessing creditworthiness.

These models are used to classify applicants into two groups: those with good credit who are approved and those with bad credit who are rejected. Key attributes including age, wealth, and military status are used for classification, or historical data of candidates who have been accepted and rejected in the past is analyzed. [15] Credit scoring models play a key role in the lending process, serving as a key tool for assessing credit risk. These models assess the financial viability of potential borrowers by analyzing specific variables and macroeconomic factors. Banks rely on credit scoring models as a primary method to determine the creditworthiness of applicants and ensure informed lending decisions. [16] Credit scoring has gained significant importance as it helps the credit sector to increase liquidity, protect loan collections, reduce potential risks, and support more effective management decisions. Due to the increasing focus on credit scoring, banks and researchers have developed various advanced techniques, known as credit scoring models, to address the challenges faced during the rating process. [17] Credit scoring techniques have been developed for various applications in various industries. In addition, predicting customer risk and reducing the likelihood of loan default have emerged as a key function of credit scoring, which helps financial institutions, especially banks, maximize and sustain potential profits from borrowers.

Credit scoring has advanced significantly since the early 21st century, due to technological advances that have brought about advanced scoring techniques such as Area under the receiver operating characteristic (ROC) curve and GINI coefficient. Furthermore, rapid advances in computer technology have significantly streamlined the implementation of credit scoring models, making them more efficient and accessible than ever before. [18] Financial institutions often use credit scoring models to classify loan applicants as low risk (good) or high risk (bad). These models have several benefits, such as reducing credit analysis costs, speeding up the loan approval process, ensuring efficient debt collection, and minimizing potential financial risks. [19] According to empirical data from real-world case studies, cost-sensitive learning consistently yields higher returns than cost-insensitive techniques. Interestingly, much of the literature does not address credit scoring from a profitability perspective. We provide insightful analysis and best practices to develop this case study by contrasting several methods for handling missing FICO or Equifax scores are examples of external credit risk scores.

Although a significant percentage of applicants may not have access to these scores, they are often used in consumer credit applications. [20] Although extensive research has been conducted on credit rating models for financial institutions, progress in developing such models for the microfinance sector has been relatively limited. Furthermore, most models used in microfinance today are derived from traditional parametric statistical techniques such as quadratic discriminant analysis (QDA), logistic regression (LR), and linear discriminant analysis (LDA). This is true despite a large body of research indicating that nonparametric techniques generally outperform these traditional statistical techniques. [21]

MATERIALS AND METHOD

Among decision-making paradigms, Hwang and Yoon's TOPSIS (Priority Sorting Technique The Analytic Hierarchy Process (AHP, Similarity of Best Solution) technique is a sophisticated but powerful tool. TOPSIS is recognized for its ability to handle sophisticated multi-criteria decision making (MCDM) with flexibility and adaptability. Situations, but AHP has gained significant recognition, especially for its straightforward and user-friendly framework. Due to its ease of use and straightforward scalability, it is a preferred method for decision makers in various industries, making it suitable for situations with multiple criteria and preferences. The TOPSIS approach is carried out in several methodological steps. After vector normalization, a weighted normalized decision matrix is calculated, which first takes the center location and transforms the raw data into a similar representation.

By displaying a positive ideal situation (PIS), this method establishes the ideal situation. On the other hand, the worst-case scenario is represented by the negative best-case scenario (NIS). The main objective of the following step is to calculate the distances between each measurement. NIS, PIS, and alternatives all use a method called "boiling point normalization," which is a data balancing process. Once these separations are established, the final step is to rank the options based on how close they are to the best answer. Ultimately, the approach yields a ranking order that indicates how closely each option matches the best outcome. TOPSIS is a recommended method in complex decision-making situations because its sophisticated computational framework enables a complete and well-founded evaluation of options. Beyond mere theory, TOPSIS (Technique for Priority Ranking by Similarity to the Best Solution) has many real-world applications that touch upon many aspects of decision-making. It can be used for everything from assessing the performance of a business to comparing financial ratios between different industries and investing in advanced manufacturing technology. However, like any other analytical method, it has its limitations. The weights and practical performance ratings of each criterion are considered to be correct values in the TOPSIS standard format. This assumption can be restrictive, especially if the values are not completely stable or precise. Improving the sensitivity of the R-value has historically been a major goal of efforts to improve the original TOPSIS model. As a result, some changes have been made, in particular, more emphasis has been placed on certain criteria. New methods have also been developed, such as the "Mikiyoshi" approach, which modifies the To make the model more sensitive, the R-value formula was modified.

Although these changes are positive, some inherent problems of the framework are not fully resolved. One such problem is the well-known rank change, which is a significant drawback of TOPSIS. This occurs when an option is added or removed during the selection process, disrupting the predetermined order of options. This can result in not just a small change in ranking, but a total reversal of the relative positions of the alternatives. Depending on the dynamics of the dynamics, an alternative that was once considered the best may suddenly appear substandard in some circumstances. This disturbing trend is unacceptable to decision makers, especially when rank consistency is essential for making well-informed decisions.

To determine the average values for A1, A2, A3, A4, and A5 based on the given situations, the proximity coefficient values (Ci) for each individual can be summarized as follows:

A1: Ci = 0.4631

A2: Ci = 0.54670

A3: Ci = 0.85835

A4: Ci = 0.12085

A5: Ci = 0.45903

ANALYSIS AND DISSECTION

TABLE 1. The Role of AI in Enhancing Credit Scoring Models for Better Lending

	DATA SET			
	Income Level (INR in 1000)	Credit Score	Existing Debt (INR in 1000)	Recent Credit Inquiries
A1	500.00	750.00	200.00	1.00
A2	600.00	780.00	300.00	2.00
A3	700.00	800.00	150.00	0.00
A4	450.00	700.00	400.00	3.00
A5	550.00	740.00	250.00	1.00

The table provides a dataset that illustrates how AI can improve credit scoring models for better credit decisions. It consists of four key factors: Income level, recent loan inquiries, current debt and credit score. These variables play a key role in assessing a borrower's creditworthiness. Income level, measured in thousands of Indian Rupees (INR), ranges from INR 450,000 (A4) to INR 700,000 (A3). In general, higher income levels indicate a greater ability to repay loans. Credit scores range from 700 (A4) to 800 (A3), with higher scores indicating better creditworthiness. Another significant factor, existing debt, varies widely. For example, A4 has the highest debt (INR 400,000), while A3 has the lowest (INR 150,000), which can affect credit decisions. Recent credit inquiries indicate how often a borrower has applied for new loans. An A3 with a high credit score of 800 has no recent inquiries, which may indicate responsible credit behavior. Conversely, an A4 with a low score of 700 has had three inquiries, which may indicate financial distress. AI-powered credit models can analyze these variables more effectively by detecting patterns and predicting default risks more accurately than traditional models, leading to better lending decisions and risk management.

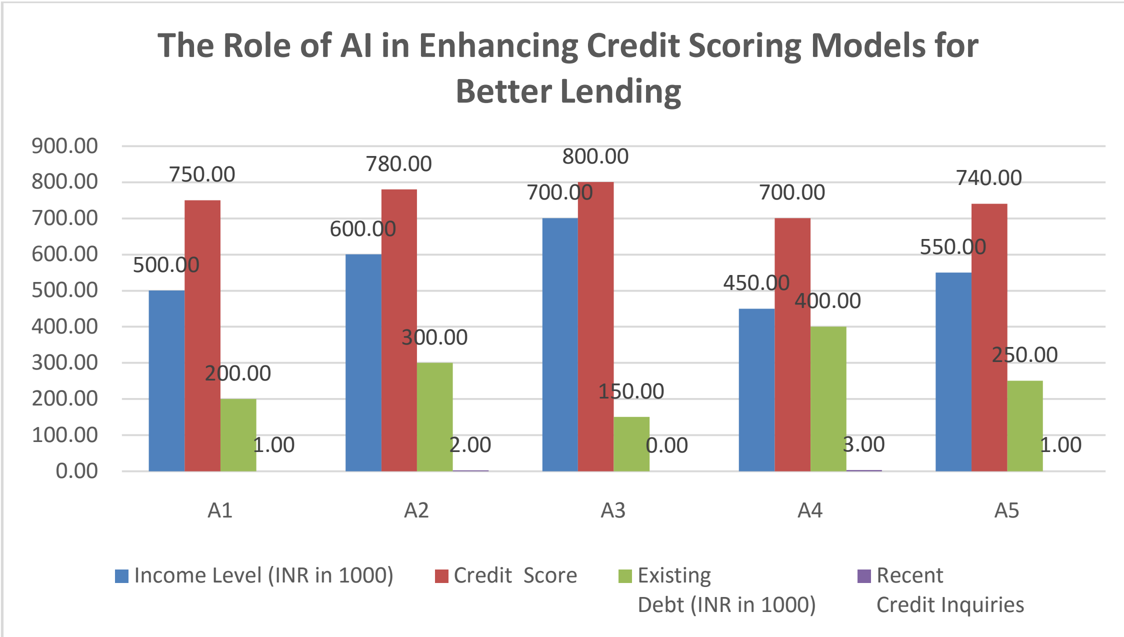

FIGURE 1. The Role of AI in Enhancing Credit Scoring Models for Better Lending

The importance of AI in improving credit scoring models for advanced credit selection is depicted in Figure 1. Five candidates (A1 to A5) are compared in a bar chart according to four important criteria: income level, credit score, current debt, and recent credit inquiries. Each variable is color-coded to differentiate their impact on creditworthiness. Income level, shown in blue, varies across applicants, with A3 having the highest income (700,000 INR) and A4 having the lowest (450,000 INR). Credit scores, shown in orange, follow a similar trend, with A3 having the highest score (800) and A4 having the lowest (700). Higher income levels are generally associated with better credit scores, indicating greater financial stability. Current debt, depicted in gray, highlights how past financial obligations affect credit ratings. A4 has the highest existing debt (400,000 INR), which may contribute to its relatively low credit score. Recent credit inquiries, shown in yellow, indicate the number of recent applications for new credit. A4 has the highest number of inquiries (3), which indicates financial distress. AI-powered credit scoring models can efficiently analyze such multidimensional data, identify risk patterns, and improve lending decisions. By integrating AI, lenders can reduce bias, improve accuracy, and make more data-driven loan approvals.

TABLE 2. Normalized Data

	Normalized Data			
A1	0.3947	0.4444	0.3266	0.2582
A2	0.4736	0.4622	0.4899	0.5164
A3	0.5525	0.4740	0.2449	0.0000
A4	0.3552	0.4148	0.6532	0.7746
A5	0.4341	0.4385	0.4082	0.2582

Table 2 presents the normalized data for five applicants (A1 to A5), where the original values from Table 1 have been scaled to a range between 0 and 1. Normalization allows for fair comparison by adjusting different variables to a common scale, ensuring that no single variable disproportionately affects the analysis. The normalized values show that A3 has the highest income level (0.5525) and the lowest number of recent credit inquiries (0.0000), indicating financial stability and responsible credit behavior. On the other hand, A4 has the lowest normalized credit score (0.4148) and the highest number of outstanding debt (0.6532), which may indicate a higher risk of default. The high value of recent credit inquiries for A4 (0.7746) also indicates financial distress. A2 has balanced scores across all factors, with moderate outstanding debt (0.4899) and a good credit score (0.4622). A1 and A5 are in the middle range, with similar trends in income and debt, but lower credit scores compared to A3. AI-powered lending models can use normalized data to identify patterns and improve risk assessment. By analyzing these measured values, lenders can make more accurate predictions and reduce bias in loan approval decisions.

TABLE 3. Weight

	Weight			
A1	0.25	0.25	0.25	0.25
A2	0.25	0.25	0.25	0.25
A3	0.25	0.25	0.25	0.25
A4	0.25	0.25	0.25	0.25
A5	0.25	0.25	0.25	0.25

All applicants (A1 to A5) are given identical weights to the four factors shown in Table 3 - income level, credit score, existing debt, and recent credit inquiries. Each factor has an equal weight of 0.25, meaning that no single variable is given priority over the others in the credit scoring process. A balanced weight distribution suggests a balanced approach where income, credit score, existing debt and recent credit inquiries contribute equally to the overall assessment of a borrower's creditworthiness. This method ensures fairness in assessing applicants without favoring one factor over another. However, in real-world situations, different lenders may assign different weights based on risk models, where factors such as credit score and existing debt may have a greater influence than recent inquiries. AI-powered credit scoring models can dynamically adjust these weights based on historical data and predictive analytics. By analyzing past credit trends, AI can determine which factors have the most significant impact on loan repayment behavior. This adaptive weighting approach improves risk assessment accuracy, helping lenders make data-driven decisions that reduce default risks while ensuring fair access to credit.

TABLE 4. Weighted normalized decision matrix

	Weighted normalized decision matrix			
A1	0.0987	0.1111	0.0816	0.0645
A2	0.1184	0.1155	0.1225	0.1291
A3	0.1381	0.1185	0.0612	0.0000
A4	0.0888	0.1037	0.1633	0.1936
A5	0.1085	0.1096	0.1021	0.0645

The weighted normalized result matrix, which incorporates an equal weight distribution from Table 3 to optimize the normalized data, is shown in Table 4 . This matrix provides a more structured comparison of applicants (A1 to A5) by adjusting the influence of each factor based on its assigned weight of 0.25. A3 has higher weighted normalized values for income (0.1381) and credit score (0.1185), which reinforces its strong financial position. However, its current debt value (0.0612) is lower, indicating a manageable debt burden. Notably, A3 has a value of zero for recent credit inquiries, indicating responsible borrowing behavior. A4, on the other hand, has higher weighted values for existing debt (0.1633) and recent credit inquiries (0.1936). These values suggest a high financial burden and frequent applications for new loans, which may indicate a high risk of default. A2 shows relatively balanced values across all four factors, with moderate current debt (0.1225) and a competitive credit score (0.1155). A1 and A5 fall in the middle range, but have slightly lower scores compared to A3 and A2. AI-powered credit scoring models use such weighted matrices to improve decision-making, ensuring that credit decisions are based on comprehensive, data-driven assessments rather than isolated factors.

TABLE 5. Positive Matrix

	Positive Matrix			
A1	0.1381	0.1185	0.0612	0.0000
A2	0.1381	0.1185	0.0612	0.0000
A3	0.1381	0.1185	0.0612	0.0000
A4	0.1381	0.1185	0.0612	0.0000
A5	0.1381	0.1185	0.0612	0.0000

The positive matrix is shown in Table 5, where the largest values from the weighted normalized decision matrix for all applicants (A1 to A5) are given as criterion values. The best case scenario is represented by this matrix, which compares each application to the best values for income level, credit score, current debt, and recent credit inquiries. In this matrix, the highest observed values for income (0.1381) and credit score (0.1185) are consistent across all applicants, indicating that they are the optimal criteria for financial stability. Similarly, since lower debt levels are generally associated with better creditworthiness, the lowest value for existing debt (0.0612) is chosen as the best-case scenario. For recent credit inquiries, the optimal value is 0.0000, meaning that no recent credit inquiries are considered the most favorable condition for assessing financial stability. This positivity matrix serves as a reference point in credit scoring models, helping AI-driven systems compare each applicant's financial profile to the best standards. By using such a structured approach, AI can calculate deviations from optimal values, allowing lenders to assess risk more effectively. This ensures that lending decisions are based on a well-defined, data-driven methodology that prioritizes financial responsibility and reduces default risks.

TABLE 6. Negative matrix

	Negative matrix			
A1	0.0888	0.1037	0.1633	0.1936
A2	0.0888	0.1037	0.1633	0.1936
A3	0.0888	0.1037	0.1633	0.1936
A4	0.0888	0.1037	0.1633	0.1936
A5	0.0888	0.1037	0.1633	0.1936

The negative matrix, showing the least desirable values for each factor from the weighted normalized decision matrix, is shown in Table 6 . This matrix sets the worst-case criteria, allowing for a comparative analysis of how far each applicant deviates from the least desirable financial conditions. The lowest observed values for income status (0.0888) and credit score (0.1037) are assigned to all applicants, indicating a weak financial condition in these categories. Similarly, the highest value for existing debt (0.1633) indicates a very high relative debt burden, as higher financial obligations increase the risk of default. The worst-case scenario for recent credit inquiries is set at 0.1936, suggesting frequent applications for credit, which may indicate financial instability. This negative matrix serves as an important reference point in AI-driven credit scoring models. By measuring the distance between an applicant's financial data and the values in both positive and negative ranks, lenders can determine how closely an individual matches the profile of an ideal borrower, or how risky they are. AI uses this structured approach to refine lending decisions, ensure applicants are accurately assessed, reduce default risks, and encourage responsible lending practices.

TABLE 7. SI Plus & Si Negative & Ci

	SI Plus	Si Negative	Ci
A1	0.0787	0.1532	0.6607
A2	0.1443	0.0828	0.3645
A3	0.0000	0.2249	1.0000
A4	0.2249	0.0000	0.0000
A5	0.0824	0.1444	0.6366

Table 7 presents three key decision-making metrics that are essential in assessing an applicant's creditworthiness using AI-driven models – SI Plus, SI Negative, and Ci. These values help lenders determine the best candidates for loan approvals based on their financial stability and risk levels. SI Plus measures the distance between an applicant's financial profile and the ideal (positive) reference point. A lower SI Plus value indicates a closer proximity to ideal financial conditions. Among applicants, A3 has an SI Plus of 0.0000, meaning it is perfectly aligned with the most desirable financial profile. In contrast, A4 has the highest SI Plus of 0.2249, indicating a significant deviation from the ideal scenario, which may indicate higher credit risk. SI Negative measures the distance from poor (negative) financial conditions. A higher SI Negative value indicates that the applicant is further away from financial instability. A3 has the highest SI negative (0.2249), which reinforces its strong creditworthiness, while A4 has the lowest (0.0000), which means it is very close to the least desirable financial conditions, making it a high-risk candidate. The final creditworthiness index, Ci, is calculated as A with a higher Ci value indicating stronger creditworthiness. A3 has the highest score (1.0000), which makes it a more suitable candidate for lending. A1 (0.6607) and A5 (0.6366) have relatively high scores, making them moderate-risk applicants. In contrast, A4 has the lowest score (0.0000), which means it is the least suitable for lending, while A2 (0.3645) falls in the lower range. By using these AI-driven metrics, lenders can make data-driven lending decisions, ensuring loans are approved for financially stable individuals, and reducing default risks.

TABLE 8. Rank

	Rank
A1	2
A2	4
A3	1
A4	5
A5	3

Table 8 provides a ranking of applicants based on their overall creditworthiness (A1 to A5), derived from the Ci values in Table 7. The ranking system helps lenders determine which applicants are most suitable for loan approval by assessing financial stability, existing debt, and recent credit behavior. A3 ranks first, indicating that it has the strongest financial profile of all applicants. This is consistent with its Ci score of 1.0000 in Table 7, which indicates minimal financial risk. A3 shows a high income, excellent credit score, low current debt, and no recent credit inquiries, making it a more reliable candidate for lending. A1 ranks second with a Ci score of 0.6607. This means that A1 is still a strong candidate for a loan, but is slightly riskier than A3. It may have moderate existing debt and some credit inquiries, which may have affected its ranking. A5 ranks third, with a Ci score of 0.6366. While A5 is a relatively good candidate, its slightly lower ranking indicates a higher level of existing debt or recent credit inquiries compared to A1 and A3. A2 is in fourth place, with a Ci score of 0.3645. This score places A2 in the moderate-risk category, meaning the applicant may have a high level of existing debt or a less favorable credit score. Lenders may need to do further analysis before approving a loan. A4 has the lowest ranking (fifth place), with a Ci score of 0.0000. This indicates significant financial risk due to high existing debt, low income, frequent credit inquiries, or a combination of these factors. A4 is not a very suitable candidate for lending. By using AI-powered ranking models, lenders can make informed decisions, ensuring that loans are made to financially stable individuals, and reducing default risks.

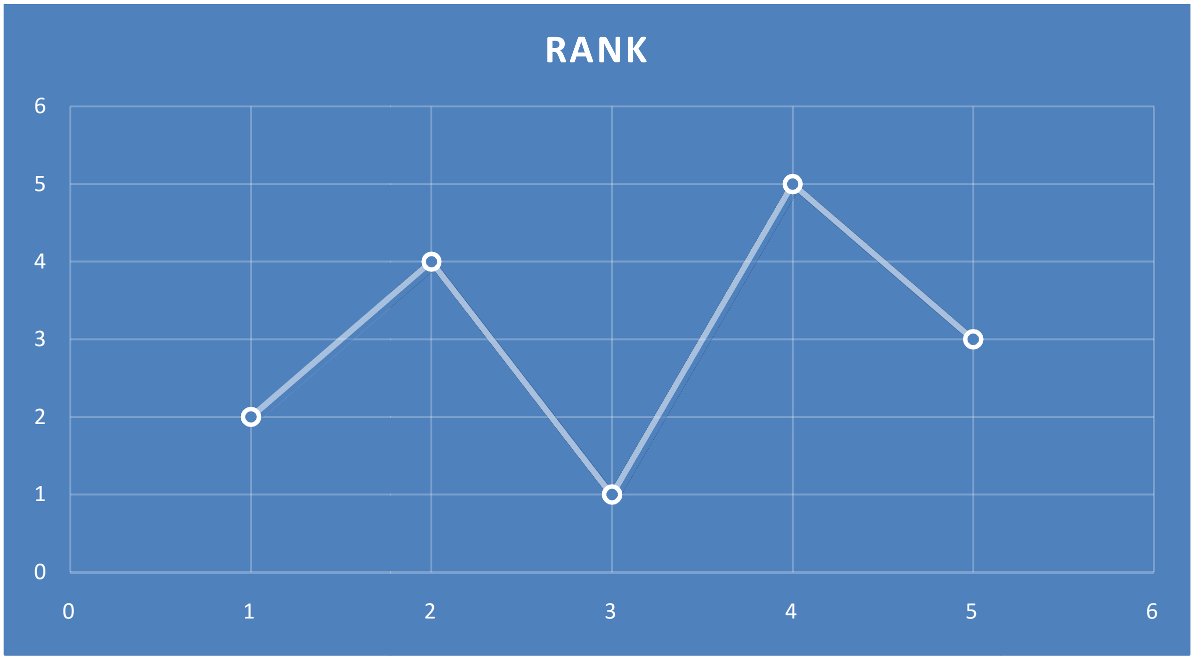

FIGURE 2. Rank

Figure 2 displays the ranking of applicants based on their creditworthiness (A1 to A5). The graph helps illustrate how each applicant compares in terms of financial stability and suitability for lending. The x-axis represents applicants, while the y-axis represents their ranking, with lower values indicating better creditworthiness. A3 has the lowest ranking value (1), making it the top-ranked applicant. This means that A3 has the most favorable financial profile, with strong income, a high credit score, minimal current debt, and no recent credit inquiries. Its position at the lowest point on the graph confirms that it is the least risky applicant for lending. A1 ranks second (2), indicating a strong financial position, but slightly weaker than A3. The graph shows a rise from A3 to A1, indicating a slight increase in financial risk. A1 may have moderate existing debt or few credit inquiries, which affects its overall ranking. A5 is ranked at 3, which reflects moderate creditworthiness. The graph shows a slight decline from A4 to A5, indicating an improvement in creditworthiness. However, A5 may have some financial risks that require further evaluation before loan approval. A2 is ranked at fourth (4), which places it in the lower half of creditworthiness. At this point, the graph rises again, indicating increased financial risk. A2 may have high debt or frequent credit inquiries, making it a less ideal candidate compared to A1 and A3. A4 has the highest-ranking value (5), making it the least creditworthy applicant. The peak at this point on the graph confirms that A4 presents a high financial risk, which may be due to high existing debt, low income, or frequent credit inquiries. This ranking visualization helps AI-driven lending models make accurate, data-backed lending decisions.

CONCLUSION

Integrating AI into credit scoring models has significantly improved the accuracy and efficiency of risk assessment in the financial sector. Traditional credit scoring methods, while useful, have limitations in handling large amounts of data, adapting to changing financial environments, and accurately predicting default risks. The most advanced strategy is provided by AI-driven methods such as machine learning and neural networks that use big data analytics, pattern recognition, and real-time learning capabilities. One of its key benefits is reducing the skill biases of AI-driven credit scoring algorithms and improving decision-making transparency. Traditional models often rely on predefined parameters that may not fully capture an applicant's creditworthiness. AI, on the other hand, continuously refines its predictions by analyzing historical and real-time data, ensuring a more comprehensive risk assessment. Furthermore, AI-driven models offer improved efficiency, allowing financial institutions to automate loan approvals, optimize resource allocation, and enhance the customer experience. The findings of this study show that AI-driven credit scoring systems significantly reduce financial risk by accurately classifying borrowers based on their credit profiles. Applicants with strong financial stability identified by AI models receive better credit opportunities, while high-risk applicants are appropriately filtered out. In addition, the use of AI helps identify potential defaulters at an early stage, allowing banks to implement preventive measures such as tailored repayment plans or alternative loan solutions. Despite these advantages, there are challenges in implementing AI-based credit scoring models. Regulations, algorithmic bias, and data privacy issues all need to be carefully considered. To maintain transparency in AI-driven decision-making processes, financial institutions must ensure they adhere to legal and ethical standards.

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