AI impact on traditional credit scoring models

ISSN 1857-9973 UDC 336.77:303.22]:005.52:005.334

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Abstract

Credit scores are an integral part of a bank's lending process because they provide insight into the creditworthiness of each borrower. The traditional credit scoring models offer a standardized approach, but they come with certain shortcomings. AI and machine learning credit scoring models overcome the negative aspects of traditional models while offering banks and borrowers more accurate techniques for risk assessment. Even though AI-powered models are superior to the traditional, they do come with certain challenges related to potential bias, transparency, privacy, and regulatory compliance. It is anticipated that in the future, hybrid credit scoring models will most likely be developed by banks in their efforts to emphasize the advantages and reduce or eliminate the shortcomings of the different models.

Keywords: AI, credit score, banks, creditworthiness risk assessment,

1. Introduction

A credit score is a crucial element in banking operations and activities. This score is an integral part of the lending process because it quantifies the creditworthiness of a borrower and assesses the risk associated with loan repayment. Advances in AI and machine learning opened up opportunities for modifying and adapting the current credit scoring models which have certain shortcomings in the way they estimate the credit score. AI-powered credit scores can provide a more accurate estimate of creditworthiness because it uses traditional and alternative data in the assessment process.

Consequently, the manner in which AI impacts the credit scoring process should be examined, and potential shortcomings should be identified. While AI models offer the inclusion of the unbanked population, bias might appear depending on the historical data used. Moreover, AI models easily adapt to changes in the surroundings or factors used, which is not the case with traditional scoring models. Overcoming the drawbacks and enhancing the advantages of both models indicates that banks will be focused on developing hybrid credit scoring models by employing traditional and AI-based techniques.

2. Traditional credit scoring models

The core activities of taking deposits and issuing loans imposes the need for banks to develop suitable methods to manage different types of risks. When it comes to mitigating credit risk and reducing the possibility for default of the borrower banks have developed credit scoring models.

The purpose of these credit scoring models used in risk assessment is to cope with the challenges arising from potential information asymmetry that exists during lending activities (Huang, et al.,2020).

Traditional credit scoring models have been the cornerstone behind bank's efforts to evaluate borrowers and mitigate credit risk. In their efforts to assess the creditworthiness of a borrower, banks traditionally depend on methods that enable them to examine the financial history, collateral level, and soft information (Huang et al., 2020). The traditional methods for credit risk evaluation are generally focused on default probability, where different weights are assigned to different characteristics (Marletta, 2022). Namely, banks, in their role as lenders, estimate the probability that a borrower will not pay the obligations for a loan (Hong Kong Monetary Authority, 2020).

Accordingly, credit scoring models represent statistical techniques that integrate different characteristics as input in the assessment and provide an output in the form of a score that indicates the level of borrower's creditworthiness (Wendel & Harvey, 2006). By using mathematical models, banks are able to quantify the expectations about possible borrower behavior associated with the possibility of loan default or bankruptcy (Hong Kong Monetary Authority, 2020).

The obtained credit score is then used in the decision process for a specific credit application, which may be in the form of an auto-decision or a score used by the relevant employees (Wendel & Harvey, 2006; Hong Kong Monetary Authority, 2020).

Credit scores are estimated using advanced statistical models that are used to process different types of data. The credit assessment models are based on data gathered from credit bureaus and borrower's behavior in the past. Credit bureaus collect various types of data associated with the borrower's financial history. Using credit bureau data, banks can examine the following: payment habits, credit utilization level, types of accounts owned by the borrower, payment history, length of credit history, number of credit cards, outstanding loans, debt-to-income ratio, and new credit inquiries.

Out of the aforementioned factors, banks assign the highest weight to the payment history that shows the borrower’s behavior in relation to repaying previous loans. Credit utilization level indicates the amount of credit used compared to the available credit limit, and banks consider a lower utilization ratio to be better. Having a credit history is perceived as a positive aspect by banks, and in general, the longer the credit history, the better. Not having a credit history would reflect negatively on the overall credit score. In some countries, credit inquiries are recorded in the borrower's file. Borrowers with frequent inquiries could be perceived as riskier by the banks. Banking institutions may use different types of ratios in the process of evaluating the riskiness level of a credit applicant. The debt-to-income ratio is a commonly used ratio in credit analysis. As the name implies, this ratio estimates the level of current debt against the borrower's income level.

In the process of calculating a credit score, a specific weight is assigned to each factor used in the analysis. The obtained credit score is expressed as a number with values between 300 and 850. A credit score of 300 indicates a high-risk borrower, which shows a higher possibility of default. On the other hand, a credit score of 850 will be assigned to low-risk borrowers with a lower risk of default. The numerical value and the range for the credit score may differ between countries. The value and category of credit score used by banking institutions also have an impact on the loan terms, such as interest rate, level of collateral, repayment terms, etc. (FasterCapital, 2024).

Banks have been using traditional methods for the evaluation of borrowers' creditworthiness for a long time, and there are many similarities in the methods used by banks in different countries. Nevertheless, these methods have been criticized for their limitations and inadequacy in the estimation of scores for borrowers without prior history. Traditional methods might have a high degree of subjectivity, and they rely heavily on historical data in the assessment process, which is not suitable for borrowers with no financial history (Anil, et al., 2021). Hence, limited scope is a limitation in the functioning of traditional credit scoring models due to their high dependence on credit bureau data, which excludes potential borrowers with limited or no credit history to obtain a loan or get a loan with favorable terms.

Another limitation is the factors that are the primary focus for determining a credit score. Namely, the traditional scoring models incorporate different factors, but they don't consider important factors such as income level, employment, current situation, purpose of the loan, or anticipated financial potential (FasterCapital, 2024). This is imposing additional burden for banks in process of evaluating credit applications as they need to include other relevant factors which are not accounted for in the credit score.

The inability to account for factors that might affect the repayment ability is also a shortcoming of the traditional scoring models. Unexpected expenses, potential job loss, or changes in the income level are important determinants of a borrower's ability for on-time loan repayment. Moreover, adequate financial behavior is also not incorporated in the current credit scoring models. Aspects such as on-time payments of utilities and rent and saving or spending habits are important determinants for future loan repayment, but they are often excluded from the credit scoring techniques.

The historic bias that occurs is also a major shortcoming of the current credit scoring models used by banks. The problem of historic bias is that the risk assessment is based on historical data and may cause the occurrence of past biases in the pending process. Hence, certain groups might be subject to lower scores even though they might have a higher level of creditworthiness (Milkau, 2021). Moreover, the borrower's past behavior has a major impact on the score, but it disregards future prospects, meaning that a current creditworthy borrower could receive a lower score due to past mistakes reflected in the credit bureau. Using historical data to anticipate future probabilities for default is also considered to be a limit of the credit scoring models (White, 2023). When focusing on past behavior to predict potential future risk, the model doesn't capture the effects of adverse economic changes or changes in the borrower's circumstances.

Although, traditional credit scoring models have multiple limitations they are largely used and acknowledge by banks to evaluate probability of default for credit applicants because they offer a standardized approach. Hence, banks are able to have consistency when assigning credit scores. Also, there is consistency between banks in the way they estimate credit scores. However, due to the limitations of current credit scoring models, creditworthy borrowers might get denied a loan or pay higher interest rates.

3. AI applications in credit scoring

Technological advances and advances in the field of Artificial Intelligence (AI) have opened up new opportunities for enhancing business processes in different industries. The financial sector, especially the banking sector, has swiftly adopted the implementation of AI-based solutions to improve efficiency in labor-intensive processes and operations such as customer care. However, AI technology can impact processes associated with credit application and analysis, which could ease the decision-making process and improve the assessment of customers' risk levels (Gsenger & Strle, 2021).

The rise of big data enables banks to make meaning of the vast amount of data they collect on a daily basis. Accordingly, combining AI solutions and machine learning developments with the huge amount of available financial and alternative data offers banks opportunities for better estimation of borrowers' creditworthiness (Wijaya & Nidhal, 2023). Hence, banks can revamp the current credit scoring system and gradually move away from or at least enhance their traditional scoring systems based on the loss and default models (Wijaya & Nidhal, 2023). Moreover, the degree of impact AI can have on procedures related to credit assessments can augment banks' processes and activities (Sadok, et al., 2022).

Significant impact can be experience in areas such as risk management, credit scoring process, debt collection, analysis associated with changes in the economic conditions, and identification of potentially fraudulent activities (Sadok, et al., 2022; Khemakhem & Boujelbene, 2017). AI and machine learning can be utilized by banks to augment financial services and activities related to pre-approval, credit underwriting, and investment, leading to profit maximization (Tyagi, 2022).

A notable use of enhanced credit scoring models based not only on traditional but also on alternative data can be found within the fintech industry. Innovative and technologically advanced fintech companies use AI-based solutions to analyze data from different sources, develop alternative credit assessment models, and determine potential risks (Shenoy, et al., 2018). Through the application of AI and machine learning credit scoring models, fintech companies are able to assess the creditworthiness and, based on the AI score, approve credit to borrowers excluded with the traditional models (Langenbucher & Corcoran, 2022). Accordingly, the aforementioned points out the ability of AI to deal with huge quantities of data as a result of the advanced algorithms leading to better categorization of low-risk and high-risk borrowers (Hurlin, et al., 2024). By enhancing the predictive capabilities of the credit scoring system, banks and other financial institutions might expect a decrease in the number of non-performing loans (Hurlin, et al., 2024). The technologically advanced models based on AI and machine learning not only enhance the lending decision but can also reduce operational costs (Shenoy, et al., 2018; Khemakhem & Boujelbene, 2017),

4. Potential benefits and challenges of AI in credit scoring

The application of AI technology in credit scoring should bring numerous benefits not only for banks but also for borrowers. For banks, AI should augment the accuracy of risk assessment, which will cause a decrease in the number of non-performing loans. Moreover, the AI-powered model's capability to incorporate alternative data on top of traditional data will expand the potential customer base through the inclusion of unbanked customers (Simumba, et al., 2018). Also, the creditworthiness of borrowers without credit history can be realistically assessed with the utilization of alternative data. The aforementioned is a benefit arising for banks as well as for customers because under the traditional scoring models, no credit history is associated with a high-risk score.

Utilization of AI-based credit score models will make it easier for banks to set an adequate interest rate for the associated risk profiles, avoiding overpricing lower-risk or underpricing high-risk borrowers. In addition, borrowers will benefit from AI credit scores in a way that they will get better terms on their loans. Another benefit is that AI can rationalize the credit approval process through the automation of data analysis and decision-making activities. This will result in swift loan approvals and an increase in customer satisfaction. The technology behind AI-powered credit score models is designed in a way that it is in the process of continuous learning based on the new data. Accordingly, an AI-based model is able to adapt to changes in the economy or changes in lending practices and procedures. Also, the learning and adaptability of AI models enable banks to detect changes in certain customer segments or even identify new segments. The following table provides an overview of the benefits of AI-based credit scoring models.

Table 1: Overview of benefits brought by AI-powered credit scoring

Benefit	Explanation / Effect
Realistic credit scores	Potential borrowers without credit history will not be assigned a “high risk” score automatically and get rejected or get hit with unfavorable loan terms. Instead, AI will conduct more realistic assessment of their risk profile and calculate adequate score.
Increased accuracy	More accurate credit scores will lead to lower levels of non-performing loans.
Expand customer base	Financial inclusion of unbanked and underbanked entities. Borrowers who were assigned low credit scores can now receive more accurate scores based on alternative data.
Improve the process of defining loan terms (personalized loan terms)	By combining traditional and alternative data, AI models are able to make adequate risk assessments of borrowers' creditworthiness. Accordingly, banks will be able to set associate interest rate based on the real risk level. Moreover, banks will be able to personalize additional loan terms as future income prospects, employment status, and economic conditions are considered when defining credit scores.
Rationalization of the credit approval process	• Automation of data analysis • Automation of the decision-making process The automation of processes will reduce the time from loan application to loan approval. The faster and simpler process will have a positive impact on customer satisfaction.
A high degree of adaptability of credit score models	Machine learning algorithms are able to continuously learn and adapt to changes reflected in the new data. Hence, credit scores will not become obsolete, and they will be up-to-date representations of borrower's creditworthiness.

Aside from the aforementioned benefits, the development and implementation of AI-based credit scoring models are faced with numerous challenges. First and foremost, AI and machine learning models can be highly complex, and understanding how a specific score is estimated can be challenging. This is especially important when it comes to clients whose loan application was rejected. Banks might face difficulties in explaining the rationale behind their rejection to the borrowers and to the regulators. Furthermore, a data bias poses a challenge when utilizing AI algorithms. Potential historical biases in the data used for training the AI model might cause inaccurate credit scores and unfair or discriminatory lending practices (White, 2023). Regulatory challenges arise because the regulatory framework and standards for using AI-based solutions are non-existent or are not clearly defined. Consequently, a lack of adequate and detailed regulations and standards might raise concerns about the accountability, fairness, privacy, and inappropriate use of sensitive data (Addy, et al., 2024). Ethical issues are yet another challenge that is associated with AI credit scoring models. The utilization of alternative data and personal data initiates privacy concerns and concerns about the existence of potential discrimination due to factors that are not directly associated with a borrower's creditworthiness.

5. Traditional vs. AI-powered credit scoring models

Although they have the goal to determine the risk levels associated with different borrowers, there are vast number of differences in the way a credit score is determined between traditional and AI scoring models. Among the first differences evident between the two types of credit scoring models is the data used to evaluate the creditworthiness of a borrower. Table 2 presents the type of data used for credit scoring by traditional models and AI algorithms.

Table 2: Data used for credit scoring

Data category	Data type	Credit scoring application
Traditional	Bank transactional data	Records of late payments on current and past credit, loan amounts and loan purpose, credit history
	Credit bureau checks	Number of credit inquiries
	Commercial data	Financial statements, number of working capital loans, and others
Alternative	Utilities data	Records of on-time payments as an indicator of creditworthiness
	Social media	Social media data with possible insights into consumer lifestyle
	Mobile applications	Mobile payment systems with possible insights into consumer behavior
	Online transactions	Granular transactional data with possible detailed insights into spending patterns
	Behavioral data	Psychometrics, form-filling

Source: World Bank Group (2020) quoted in Wijaya, T. & Nidhal, M. (2023). International Experiences with Innovative Credit Scoring. Center for Indonesian Policy Studies Discussion Paper No. 14.

As it can be seen the traditional credit scoring models primarily rely on credit bureau checks, transactional data or commercial data. This type of models assigns high level of importance on past loan repayment behavior, credit history, purpose of the loan, current credit inquiries, financial ratios, etc. In essence, the traditional models are focus on detecting inadequate past behavior to make risk assessment of credit applicants.

On the other hand, AI algorithms incorporate historical data used by traditional models, but they combine this data with new, alternative types of data gathered from multiple different sources. AI models evaluate utilities data in terms of on-time payments as a positive signal for higher creditworthiness. Moreover, social media data is analyzed to better understand borrower's lifestyle and spending habits. Saving and spending habits are also examined through the utilization of data from bank accounts, mobile payment systems, and online transactions. AI models integrate psychometrics data to further examine borrower’s creditworthiness by looking at characteristics such as borrower’s responsibility, self-control, self-efficacy, and many more factors (Duman, et. al., 2023). The difference in used data types is not the only difference between the traditional and machine learning models for defining credit scores. Table 3 provides an overview of the major differences between traditional and AI credit scoring models.

Table 3: Overview of major differences between traditional and AI credit scoring models

Feature	Traditional Credit scoring	AI-based credit scoring
Model employed	Statistical models; Linear regression model	Machine learning algorithms: Decision trees, Neural Networks Support vector machines
Credit score results	• Potential for biases due to dependence on historical data • Borrowers without a credit history are receive a "high risk" score • Lower accuracy	• Decrease in the number of rejected good borrowers • Reducing the possibility for approval of potentially high-risk borrowers • Include previously excluded borrowers • Higher accuracy
Access to credit	Borrowers with limited or no credit history are commonly rejected because they receive a "high risk" credit score.	Increases financial inclusion through the use of alternative data to calculate borrower's credit score. Underbanked entities are able to access micro-loans.
Updating frequency	The credit score is not regularly updated because it usually relies on new credit reports, implying that it can be based on obsolete data.	The credit score is monitored and adjusted in real-time based on the latest data about financial behavior, economic conditions, and borrowers' behavior. Consequently, banks might be able to offer flexible loan terms and make adjustments as needed.
Ease to understand the assigned credit score.	A black box model makes it difficult for someone to understand how credit scores are defined.	Easier to explain AI-based models. Borrowers are able to understand factors that are considered when estimating their credit scores.

Apart from the data type, another notable difference between the two credit scoring techniques can be found in the types of models used for performing the credit score analysis. Namely, the traditional scoring system relies on statistical models and linear regression models (Xhumari & Haloci,2023). Nowadays, with the technological advances in data science and machine learning these techniques might be perceived to be obsolete. On the other hand, AI credit scoring models utilize the power of machine learning algorithms such as decision trees, neural networks, and support vector machines (Oualid, et al., 2022; Leo, 2019). The AI models for risk assessment are more advanced in terms of technological capabilities and available features. Another difference in the functioning of the two models can be identified in the credit score results. Under traditional models, credit scores may be subject to bias because of the heavy reliance on historical data. In addition, borrowers lacking credit history are almost instantaneously assigned a "high risk" score.

Contrary to the traditional models, AI models contribute toward a decrease in the number of good borrowers who were denied a loan. Also, the usage of different types of data enables AI algorithms to better analyze creditworthiness and decrease the possibility for loans to be approved to high-risk borrowers. If a credit score is determined using the traditional models, the update is commonly performed when new credit reports are delivered. This means that the current credit score might be based on old data that is not relevant; hence, it doesn't reflect the true creditworthiness of a borrower. An AI-based credit score is superior in this area because it is updated frequently. AI algorithm monitors the credit score and makes necessary adjustments based on the latest data about the different factors included in the analysis. The adjustments are made in real-time, which indicates that the current credit score incorporates all relevant changes in factors such as financial behavior, spending, economic conditions, etc.

Overall, it could be noted that traditional models have been used by banks for decades because they are reliable and offer a standardized way of estimating borrower's creditworthiness. However, a major shortcoming is their limited data scope. In contrast, AI-powered credit scoring models overcome the shortcomings of data used in the traditional models. The new and alternative models offer higher accuracy, real-time monitoring, and inclusion of borrowers which have been excluded with the traditional credit scoring models. Nevertheless, AI-generated scores do come with certain drawbacks in terms of data privacy, bias, and explainability.

6. Conclusion

Traditional credit scoring models are crucial for banking institutions in the process of determining creditworthiness. Even though these models have drawbacks, they offer a standardized approach to measuring and quantifying risk associated with different borrowers. Nevertheless, technological advancements and developments in the area of AI and machine learning opened up possibilities for modification and technological updates of traditional credit scoring models. AI-powered credit scoring enables banks to overcome the shortcomings of current risk techniques and augment the process of estimating credit scores.

The AI algorithms have the potential to enhance the risk assessment, reduce loan approval time, promote financial inclusion and reduce operational costs. Nevertheless, a credit scoring system based on AI technology imposes the need for addressing challenges associated with potential bias, transparency, and regulatory issues. Aside from the challenges, the application of AI has the potential to revolutionize the credit scoring process in banks through the development of models that offer higher accuracy, efficiency, and flexibility.

Considering the advantages and shortcoming of the traditional and AI-power models for assessment of creditworthiness might be an indicator that in the future, credit scores should be based on hybrid models.

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