

# The Application of Artificial Intelligence in Credit Assessment and Dynamic Risk Monitoring

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**Abstract.** The traditional credit assessment system relies on static financial data and historical credit records and has inherent limitations such as financial exclusion and lagging in risk early warning. Credit assessment and risk monitoring have been fundamentally reshaped in recent years, fuelled by advances in artificial intelligence and big data analytics. This article provides a systematic review of how artificial intelligence is applied in credit assessment and dynamic risk monitoring. It delves into the innovative breakthroughs concerning data dimensions, model construction, and monitoring paradigms. Research shows that AI has achieved a paradigm shift from static assessment to dynamic monitoring by introducing alternative data (for example social behavior, transaction records, etc.) and advanced algorithms (such as natural language processing and reinforcement learning), significantly enhancing the accuracy, timeliness and inclusiveness of assessment. This study scrutinizes critical challenges—such as data privacy, algorithmic fairness, and model interpretability—while also mapping out future trajectories for public data infrastructure and intelligent regulatory frameworks. Its conclusions are intended to guide further academic research and inform practice within the domain.

**Keywords:** Artificial Intelligence (AI), Credit Assessment, Dynamic Risk Monitoring, Inclusive Finance.

## 1. Introduction

Finance is the lifeblood of the modern economy, and credit risk assessment is the cornerstone for the stable operation of the financial system. The traditional credit assessment system relies on static financial data and historical credit records. Despite its development, it has always been difficult to break away from its inherent limitations: on the one hand, it excludes a large number of disadvantaged groups lacking credit history (such as farmers and freelancers) from the service threshold, forming a profound "financial exclusion" phenomenon [1]. On the other hand, its lagging assessment frequency makes it difficult to capture the real-time changing credit status of users, resulting in financial institutions being unable to effectively warn and intervene in sudden risks.

In recent years, the rapid development of AI (AI) and big data technologies has provided a revolutionary toolbox for solving the above-mentioned predicament. With high-performance complex algorithms and data mining technologies, AI can accurately identify the correlations and dependencies in financial behaviors, thereby achieving a comprehensive assessment of credit qualifications and providing more precise risk pricing mechanisms [2]. AI can also serve as an on-demand credit risk assessor, enabling lenders to dynamically adjust models based on real-time financial behavior [3]. In addition, AI can also enhance affordability and expand credit coverage. By mining Alternative Data to reshape the credit profile and achieve real-time risk monitoring through dynamic behavior analysis [4], AI is driving a fundamental transformation of the credit assessment paradigm from "static, isolated, and post-event" to "dynamic, panoramic, and in-event". This transformation not only concerns the improvement of technological efficiency but also holds profound strategic significance for promoting inclusive finance and serving the real economy.

In the traditional credit assessment system, relying on organized data and statistical models for credit assessment have credit evaluation and default prediction techniques traditionally done. A comprehensive score was generated by integrating data such as credit records, debt levels, repayment history and income [5]. This score can assess the borrower's risk level and assist lending institutions in deciding whether to lend and set specific terms. Although traditional methods are widely applied,

they still have limitations. The drawback of relying on a single variable to assess the risk of an individual or an enterprise lies in the fact that the real world is far richer than the internal data, and the information pertaining to financial hazards may not precisely represent the actual risk scenario. This is due to the fact that these models are fixed and excessively depend on past data and pre-set rules, their responses to borrower behavior or overall economic changes are relatively poor. Furthermore, traditional models may contain biases and neglect new borrowers, youthful borrowers, or populations in developing markets, resulting in a lack of inclusivity in the overall process.

With the progress of The Times, AI has gradually emerged in the financial industry, becoming a powerful engine driving change, especially excelling in the fields of risk assessment and credit scoring. AI-based models can analyze massive and diverse datasets, including non-traditional data sources such as social media dynamics, real-time payment transactions, and online behaviors. Unlike traditional models, AI systems can continuously learn and adapt to new data, providing more accurate and dynamic credit evaluations. This technology not only effectively eliminates prejudice and enhances the accessibility of financial services for vulnerable groups, but also significantly optimizes the overall risk control efficiency of the financial industry. It also provides technical possibilities for the transformation of the traditional credit assessment system.

However, current research mostly focuses on the optimization of specific model algorithms, lacking a systematic review and reflection on the application panorama of AI in this field. Against this backdrop, this article aims to conduct a comprehensive review of the innovative applications of AI-driven credit assessment and risk monitoring. At present, promoting the deep integration of AI and credit assessment has been regarded as an important path to empower high-quality economic development [6]. This article will first analyze the inherent flaws of the traditional system, then systematically expound the core breakthroughs of AI technology in the data dimension, model construction and monitoring paradigms, and by comparing typical domestic and foreign practice cases, summarize their achievements and challenges. Finally, it will put forward prospects for future research directions and regulatory trends, providing references for academic research and industrial practice in related fields.

## **2. Innovative Dimensions of AI-driven Credit Evaluation: From Data to Model**

### **2.1. Data Innovation**

In the credit evaluation system driven by AI, the data used is not limited to traditional data, but rather alternative data is employed for assessment. Alternative data includes non-traditional information such as mobile phone usage records, utility bill payments, rent payment history, social media activities, and even psychometric data [7]. By analyzing the patterns of these alternative data, AI models can build more complete credit profiles, especially for those who lack or have no traditional credit records, creating portraits of "credit white households".

### **2.2. Model Evolution**

In the credit assessment system driven by AI, the evolution of models is also an important innovation and progress of the system. Such as AIAI driven credit risk is an important innovation in the model, is to use natural language processing (NLP) technology to analyze emotional and financial behavior research [8,9]. As an important branch of AI, NLP deals with computer-human language interaction, allowing machines to analyze and interpret text and speech. In the field of credit risk modeling, NLP can be used to analyze various unstructured data sources, such as news reports, social media updates, customer reviews, and financial reports, etc. By extracting insights from these text data, financial institutions can more effectively assess a borrower's behavioral patterns, emotional predispositions, and holistic financial health.

In addition, reinforcement learning (RL), as a cutting-edge technology in the field of AI, is being widely applied in credit risk models to develop adaptive strategies [10]. This machine learning method learns the decision-making mechanism by allowing the agent to interact with the environment

and receive feedback of rewards or punishments. In the field of credit risk modeling, reinforcement learning can continuously optimize credit risk strategies based on real-time data. This enables financial institutions to adapt to the constantly changing market environment and borrower behavior patterns, which is crucial for today's rapidly developing economic landscape. For example, in the reinforcement learning process of bank credit scoring [11], basic data is input first, including credit information related to customers; Then, by using the processing reinforcement learning scoring strategy, the scoring system is processed and the credit factors are dealt with, and then the reinforcement learning model is trained based on these data. Then, in the training cycle, select actions (such as whether to lend or not, the assigned credit score range), execute based on the processing reinforcement learning score strategy, observe new states (such as customer repayment situation, default probability, etc.), and update rewards and strategies; Finally, determine whether the scoring result is valid. If it is not, feed it back to improve the scoring system. If it is valid, it indicates that the scoring system is successful and this round of learning can be stopped.

By applying advanced algorithms and machine learning techniques, AI can significantly enhance accuracy when assessing credit qualifications, more precisely predicting the possibility of borrowers defaulting on loans and reducing default rates and non-performing loans. The following table shows the comparison between traditional and AI-driven credit scoring models. These AI-driven models can continuously learn and adjust based on new data, thereby gradually improving the accuracy of predictions. This risk prediction ability enables financial institutions to proactively take countermeasures - such as adjusting loan terms, providing financial consulting services, and even rejecting high-risk applicants before they cause problems. And this advanced system can also enhance inclusive finance.

**Table 1.** Comparison between traditional and AI-driven credit scoring models.

Criteria	Traditional Credit Scoring	AI- Driven Credit Scoring
Data Source	Financial history, credit reports	Alternative data (social, behavioral, transactional)
Speed of Assessment	Slow (manual or semiautomated)	Fast (real- time, automated)
Accuracy	Moderate	High (due to dynamic learning and data variety)
Scalability	Limited by manual processing	Highly scalable with automation
Adaptability to Change	Low (static models)	High (machine learning adaptation)
Transparency	Transparent (rules- based)	Opaque ("black-box models")

Data source: [5]

As shown in Table 1, this table highlights the key distinctions between traditional credit scoring models and AI-driven credit scoring models. Traditional systems rely on limited financial data and manual processing, resulting in slower assessment speeds and generally lower accuracy. In contrast, AI-driven models utilise diverse data sources and automated analysis to deliver faster, more accurate and scalable outcomes. They can also rapidly adapt to new information through machine learning, though they typically face challenges of opacity and limited interpretability compared to transparent, rule-based traditional approaches.

### **3. From Static Assessment to Dynamic Monitoring: A Fundamental Shift in the Risk Control Paradigm**

Traditional credit assessment is like a static snapshot, only capturing the historical moments of users at the time of credit granting decisions, while post-loan risk changes become blind spots. The introduction of AI has transformed risk monitoring into a continuously updated dynamic film, achieving real-time and continuous perception and early warning of users' credit risks throughout their entire life cycle.

#### **3.1. Mechanism and Value of Dynamic Monitoring**

The core of dynamic monitoring lies in the continuous analysis and interpretation of the real-time behavior data stream of users. The mechanism is to access users' payment transaction records, APP operation logs, geographical locations and other continuous data streams through authorization, and use stream computing technology and machine learning models to calculate a series of risk indicators (such as income volatility, abnormal transaction behavior scores, sudden changes in consumption preferences, etc.) in real time. Once abnormal signals are detected (such as frequent loan applications in a short period of time, abnormal transaction time and location, or interruption of the main income source), the system can automatically trigger early warning or intervention measures, such as freezing the credit limit, triggering manual review or pushing personalized repayment reminders.

The value of this paradigm is revolutionary. It extends risk control from a single decision-making point before the loan to full-process management during and after the loan, achieving a transformation from "post-loan collection" to "in-process prevention", which greatly reduces the possibility and extent of losses caused by sudden bad debts.

#### **3.2. Typical Case Analysis**

As a benchmark of domestic digital banks, WeBank's "Weilidai" product is a model of alternative data applications. Relying on Tencent's social and behavioral data, it has built a unique credit scoring model. For "white account" users who cannot provide credit records, the model comprehensively assesses their credit status by analyzing their behavioral characteristics within ecosystems such as WeChat and QQ (such as the stability of social relationship chains, game payment behaviors, and the frequency of Tenpay usage, etc.). This model has successfully served a vast number of customer groups that traditional banks cannot reach. By the end of 2023, over 80% of WeBank's loan customers had a college degree or lower, and over 78% were engaged in non-white-collar service industries. This truly demonstrates the significant social value of AI in promoting inclusive finance transactions [12]. This system not only checks the transaction amount and merchant type but also builds a personalized behavior baseline for each user. For instance, if a user who is frequently active in Beijing suddenly makes high-frequency and large-scale purchases on their card abroad, the system will identify it as a high-risk transaction within a few hundred milliseconds and block it. Meanwhile, the system can also identify more covert gang fraud patterns, such as analyzing the transaction networks among multiple accounts through graph neural networks (GNNS) to discover potential fake card fraud or cash-out gangs. This dynamic monitoring system has reduced the credit card fraud rate by more than 50%, significantly enhancing the level of asset security.

### **4. Challenges Faced**

Although the prospects of AI-enabled credit assessment are broad, its development is still accompanied by a series of severe challenges, mainly concentrated in three dimensions: data privacy, algorithm fairness and model transparency.

Firstly, the challenges of data privacy and security have evolved from theoretical risks to an imminent regulatory compliance red line. The collection scope of alternative data has far exceeded the boundaries of traditional credit reporting, covering sensitive information such as social behaviors,

fingerprints on mobile devices, and e-commerce transaction records. Under the "notice-consent" principle established by the Personal Information Protection Law, how to ensure the legality and transparency of data acquisition has become the primary challenge. More importantly, the risks of secondary utilization and the regulations on cross-border data transmission faced in the process of multi-source data fusion analysis make financial institutions walk on thin ice when developing and utilizing data.

Secondly, algorithmic discrimination and fairness challenges are becoming invisible barriers hindering the realization of inclusive finance. The essence of machine learning models is to learn patterns from historical data. When the training data itself contains socio-economic biases (such as historical credit biases of specific regions, genders, and occupational groups), the model will solidify or even magnify them through complex feature associations. This vicious cycle of the "digital divide" is specifically manifested in the fact that groups with historically insufficient credit, due to the lack of credit records, receive lower scores in AI models and thus continue to be excluded from services, resulting in structural unfairness. Empirical research shows that in a certain consumer loan model, applicants with the same credit characteristics may have a 20% deviation in the credit limit due to differences in their place of residence.

Thirdly, the challenge of model interpretability directly restricts the practical application and regulatory acceptance of AI systems. With the wide application of complex models such as deep learning, their "black box" feature makes it difficult to trace the logic of credit decision-making. When a loan application is rejected, financial institutions have the legal obligation to provide reasonable explanations to users, but traditional explanation methods such as feature importance weights are difficult to meet the regulatory requirements of "clarity and specificity". This lack of transparency simultaneously hinders model auditing and risk screening, making it impossible for regulatory authorities to effectively verify whether the model has systematic biases or logical errors. The European Banking Authority has explicitly stipulated in the Digital Operational Resilience Act that financial institutions must ensure the auditability of AI decisions, which provides an important reference for regulatory practices in our country.

## 5. Conclusion

This article demonstrates how AI, through the integration of alternative data and sophisticated algorithms, has catalyzed a paradigm shift in credit assessment. The field has evolved from a static, lagging indicator to a dynamic, real-time process, markedly improving its accuracy, inclusiveness, and risk control efficiency. Nevertheless, it grapples with critical issues including data privacy, algorithmic bias, and model interpretability. Despite these challenges, the transformative shift driven by AI-powered credit risk models in the financial sector is an irreversible tide. By leveraging state-of-the-art technologies like natural language processing and reinforcement learning, financial institutions can develop a credit risk assessment framework that is markedly more accurate, efficient, and adaptable. These innovations not only enhance the accuracy of credit decisions but also endow financial institutions with greater flexibility and the ability to respond to changes in the economic environment. Furthermore, by reducing bias and enhancing transparency, AI-driven models are expected to make lending practices more equitable and inclusive. With the continuous advancement of technology, credit risk models driven by AI will become key tools for optimizing financial services, improving risk management, and promoting the growth of the financial industry.

In the future, there will no longer be a reliance solely on the super-large data volume of a single platform, but rather a trend towards building a public data infrastructure led by the government and involving multiple parties. For instance, the "public Data Open platforms" being explored in various regions, after obtaining user authorization, can provide more authoritative and fair government data query services for financial institutions.

The regulatory approach will also be intelligent. The "regulatory sandbox" provides a safe testing ground for innovation. Meanwhile, regulatory authorities can utilize regulatory technology tools to

directly connect with the model interfaces of financial institutions for real-time and transparent compliance testing, achieving a paradigm upgrade of "regulating technology with technology".

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