



Enterprise Credit Portrait Mining and Default Risk Intelligent Assessment Method under Digital Finance Scenario

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SUMMARY: *With the rapid development of digital finance, the mode of enterprise credit risk assessment has changed, and now also requires methods that can handle large-scale, diverse data and smart computation. The old system of credit rating has been based on the results of past financial reports and is no longer suitable for evaluating the changes and risks in modern corporate finance. This paper proposes a multi-dimensional model for mining credit reports of mining enterprises and combines structured financial data, transaction information, operating indicators, and other unstructured auxiliary data such as social media presence, online communication, supply chain dynamics, etc. By building a relatively detailed credit report, the bank can gain some information on the risk of a company's credit and its repayment ability for a loan. Algorithms that use machine learning, deep learning, ensemble models and predictive analysis are also known as intelligent default risk assessment algorithms that enhance the accuracy and flexibility of credit assessment. The following are ways to discover abnormal or complex patterns in a large amount of data early on for risk early warning, online credit assessment and dynamic portfolio management. Interoperability of digital finance platforms can support lifelong learning, automation and scalable high-frequency financial data, and maintain security, privacy and regulatory compliance. Although the above have been achieved, there are still deficiencies in the quality of data, interpretability of models, adherence to regulations, and sufficient computational resources, especially for small and medium-sized enterprises and new market institutions. Future research directions include building explainable AI systems, continuous learning, integrating multiple types of data (multimodality), and decentralized finance (DeFi) based on blockchains. At this point, the above technologies are expected to help enterprises strengthen credit risk management in the age of digital finance and provide more accurate and timely credit evaluations.*

KEYWORDS: *Distributed Learning; Cyber Threat Detection; Edge Intelligence; Secure Aggregation; Data Heterogeneity; Real-time Anomaly Detection*

1 Introduction

The rise of digital finance has changed how enterprise credit risks are assessed by altering the traditional model of evaluation based on financial statements, and now, with the help of new technological tools, big data analysis and computational intelligence are being applied (Wu, 2022). All of the above are kinds of digital finance that can help enterprises raise funds more efficiently, manage transactions in real time, and make data-driven decisions based on information: online banking, fintech platforms, peer-to-peer lending and blockchain-based financial services. However, with this rapid development, some serious problems in the

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financial industry have also arisen: the old mode of credit risk assessment relies too much on historical data and manual analysis and can no longer cope with the new forms of financial risk that have emerged in the digital economy (Sussan and Acs, 2017).

Enterprise credit reports have been introduced as a way to manage credit risk in the face of the above problems. A credit portrait is an all-encompassing, data-driven image of a company that integrates financial, operational and behavioural information. In addition to the above traditional financial indicators, a credit portrait also integrates organised data from the balance sheet, cash flow statement and transaction history with unstructured information such as digital footprints, social media behavior, and supply chain activities. Thus, it can be determined whether the company is likely to repay its debts and how risky it is going forward (Nwachukwu, 2024).

Intelligence-based default risk assessment is gradually being added to the system of enterprise credit ratings. AI, machine learning and big data analysis can reveal concealed, complicated and non-linear patterns and predictive factors in the data that have gone undetected by the previous method. Supervised learning-based credit scoring methods, unsupervised clustering for risk segmentation, ensemble models to improve predictive accuracy, and other ways will be used to build a dynamic risk assessment system in real time. In addition, by utilising alternative sources of data for behavioural and supply chain information, such as transaction records, improved prediction performance has been achieved in the model, and adaptive, data-driven credit strategies can be developed (Rishehchi Fayyaz et al., 2021).

Digital finance will add uninterrupted data collection, processing and analysis services to enhance the effectiveness of the above combined approach. Online behaviour indicators, high-frequency transaction data, and other links in the supply chain can be used to detect early warning signs of credit deterioration or default. At present, technological solutions such as cloud computing, blockchain and distributed ledger technology can be used to ensure the security, transparency and auditability of data; thus, they enhance the credibility and scalability of credit portrait mining and smart risk assessment systems (Chatterjee, 2019).

The application of the above advanced methods also has some problems. Due to the nature of the data, it is sensitive financial and operational information that needs to be high-quality and secure. The second is the problem of the low interpretability of complex AI and machine learning models; given that the decision-making needs to be transparent and explainable, it must meet regulatory requirements and the expectations of all parties involved. In addition, it is necessary to build risk assessment models that can be applied to all industries and types of enterprises universally, and at the same time, be adaptable to various circumstances in the market environment (Balaji et al., 2024).

Research on enterprise credit portrait mining in an intelligent default risk assessment framework for the digital economy. Many sources of data, models and other types will be used to build an all-encompassing system that can conduct precise, timely and flexible assessments of enterprise credit risk. This paper will also list the current limitations in the development of new technologies for enhancing the accuracy, openness and stability of credit risk management, as well as their future prospects and possibilities. Finally, the idea of a data-based credit profile and intelligent evaluation tools will help to build a safe, flexible and high-efficiency financial system for the business of new ventures in more digitalized markets (Alao, 2025).

2 Enterprise Credit Portrait Mining

General-purpose, multi-dimensional methods are used to study the financial and operating conditions, as well as other behaviors of a company based on various sources of data in enterprise credit portrait mining (Zhang et al., 2025). Traditionally, the credit risk evaluation of

a company has mainly relied on analyzing its past business conditions and calculating a few financial indices to determine the degree of credit risk; now, all-weather-based credit scoring models have been developed for assessing such risks. This way can also be used to assess whether a company has sufficient funds, how well it operates and developed over time, what the market is doing, and what kind of risks the company is facing in terms of the potential for default (Siraj et al., 2024).

All kinds of structured data, such as financial conditions and payment history of a person, are collected and organised to create a credit report. The above are quantitative indicators used to assess the financial status and ability to pay debts of a company. In addition to structured data, there is also unstructured and alternative data that can offer a large amount of information about a company's operations and interaction with the market, such as transaction and supply chain activities, social media presence, online discussions, customer reviews, etc. Adding the above sets of data can help us find more specific risk indicators, such as an abrupt increase or decrease in transaction volume, delayed payments, or negative changes in market sentiment that are not covered by the traditional indicators (Odunaike, 2025).

Collection will be carried out to process and extract features from the data, and at this time, the raw data will be transformed into practical indicators reflecting all sides of the company's credit profile. Some of the extracted features will be cash flow volatility, debt-to-asset ratio, operating efficiency, payment consistency and the extent of market coverage. Utilise all types of high-end analysis methods for the unstructured data, such as natural language processing, network analysis and anomaly detection, to uncover hidden patterns and correlations in this data, and then add the resulting findings to the credit report to provide a more complete picture of a borrower's financial situation. Together, all of the above features constitute a high-dimensional, multi-dimensional map of a company's financial and operational information, as well as behavioural data (Rashid and Choudhury, 2019).

Analysis should be carried out of credit portrait mining. By using machine learning and statistical models to extract information, divide enterprises into risk categories, and forecast future risks of financial problems and default. Clusters are created using clustering algorithms to group enterprises with the same features and reveal underlying patterns in the data. The two types of predictive models for the probability of default are regression and classification. Time-series analysis can also be applied to observe changes in financial and operating conditions over a long period to build a dynamic forward-looking credit assessment system (Dainelli and Mengoni, 2025).

The Benefits of Enterprise Credit Profile Mining are many. Collect all kinds of data and consider how a company will behave in different situations; thus, we can form a full-featured index of credit risk for the bank. It will be able to conduct proactive risk control by providing lenders and investors with an earlier warning of potential problems, and they can adjust the terms of credit or increase monitoring of high-risk projects. In addition, the strategy is also suitable for the environment of digital finance; high-frequency and real-time data are easily available here, so continuous and dynamic evaluation can be carried out, rather than periodic and static evaluation (Odunaike, 2025).

However, this way also has some problems. To ensure the accuracy of the credit portrait, the quality, reliability and consistency of the data in unstructured and alternative sources should also be guaranteed. Various Datasets need to be cleaned, transformed and standardised through advanced methods of combination. As the model becomes more complex, its reason for making decisions and compliance with regulations must also be more understandable and open to the public (Barnes and Hutson, 2024), as shown in Figure 1.

Enterprise Credit Portrait Mining

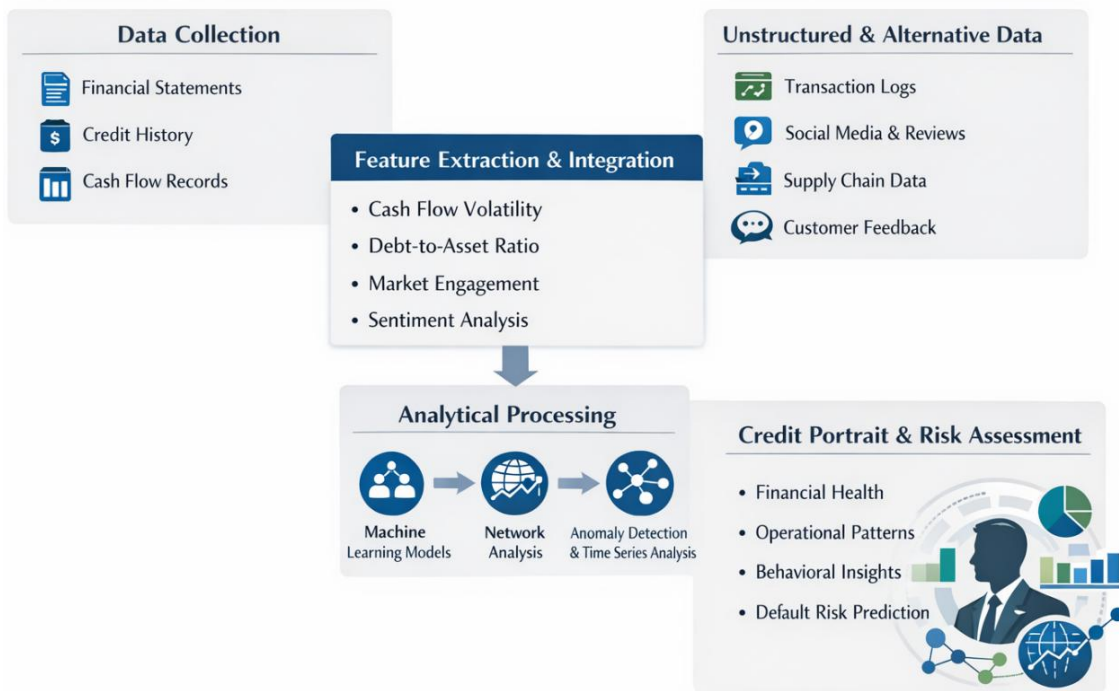


Figure 1: Enterprise Credit Portrait Mining: An All-round Evaluation of Financial Health, Operational Behavior and Market Engagement Based on Data Integration and Advanced Analytics

3 Intelligent Default Risk Assessment Methods

Recently, due to the development of good computational technology, intelligent default risk measurement tools have begun to appear and assist enterprises in enhancing the accuracy of credit risk assessment and predicting the risk of default (Alvi et al., 2024). On the other hand, the new intelligent assessment methods are based on machine learning, deep learning and other high-dimensional data and advanced statistical models to handle complex problems; traditional methods generally only use static credit scores, past financial indicators, etc., and are not highly sophisticated. Through the above methods, hidden patterns, non-linear relationships and other subtle clues in both structured and unstructured data can be extracted to enhance the early warning system for credit risk (Yanney).

Predictive Models Serve as the Foundation for Smart Risk Analysis. Logistic regression, decision trees, random forests and gradient boosting are typical examples of supervised learning algorithms that have been widely applied to predict the probability of default. Based on historical data, the model finds relationships among many characteristics of a company, such as liquidity ratios, fluctuations in cash flow, debt level, operating activities, etc., and whether it has fallen into financial distress. According to the above connections, the predictive model provides a probability of default for assessing the risk of default and aids creditors in timely decision-making and risk control measures (Faheem, 2021).

Many unsupervised learning algorithms are also used to organise the company's data and identify concealed tendencies in this data, in addition to supervised learning. The clusters of enterprises with similar financial and behavioural traits can be obtained using K-means and hierarchical clustering. Divide them into categories to identify high-risk groups and new

patterns of instability among the enterprises for targeted monitoring. Unsupervised methods are suitable for use when labeled data of historical default events are scarce or missing (Ridwan).

The ensemble model will also enhance prediction accuracy by combining the above models. Random forests, gradient boosting machines and stacking models are methods that combine the strengths of single learners to reduce overfitting. The above models can discover various types of connections among the features and offer corresponding solutions for dealing with large amounts of enterprise data. Ensemble methods can increase the sensitivity and specificity of default prediction to improve the accuracy of risk classification for optimised portfolio management (Wang and Ma, 2012).

The application of deep learning can expand the scope of opportunities for default risk assessment and process unstructured and alternative data. CNNs and RNNs can be used to analyse sequential and text data, such as transaction logs, payment history and online communication, to find temporal relationships and recurring patterns that are indicative of credit risk (Mienye et al., 2024). A model of complex interactions that have not been exposed by traditional machine learning methods can be built using deep learning models, and such a model offers an all-encompassing view of a company's financial condition.

First, the system has the function of real-time risk assessment (Xu et al., 2012). All sorts of data are being generated at the same time by various digital finance platforms, including transaction data, social media data, and supply chain data. The high-frequency data can be used to continuously update the credit score and risk level of a person through a machine learning model. Dynamically monitor for signs of abnormality promptly, adjust credit limits regularly, take timely corrective actions, and thus reduce the risk of default and improve the overall stability of the portfolio (Adams and Owen, 2024).

The above are the advantages of smart assessment; at the same time, there are some deficiencies. Interpretability is a problem; that is, complex models, especially deep-learning-based ones, are often referred to as "black boxes". Make the choice openly and comply with all relevant laws and regulations. Explainable AI technology and feature importance analysis can be used to show how a prediction is made, increasing trust in the system. Prediction error is due to a problem in the input data. Lack of data, bias in data, or noise in data will all harm the effectiveness of a model; thus, robust preprocessing, normalisation, and fusion (Nanjundan et al., 2026) should be conducted as shown in Figure 2.

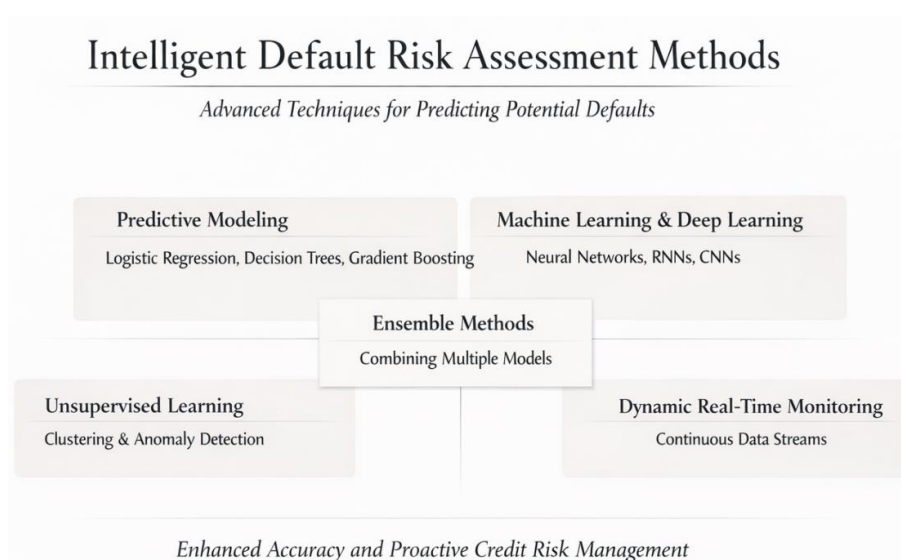


Figure 2: Framework of intelligent default risk assessment methods showing predictive modelling, machine learning, ensemble techniques and real-time risk monitoring.

4 Integration with the Digital Finance Scenario

Mining of enterprise credit reports and intelligent methods for default risk assessment have created a synergistic ecosystem that can support more accurate and timely lending decisions through real-time automated risk assessment (Ma, 2025). Digital finance services can be employed to increase the volume of high-frequency data available online banking for improving credit risk assessment. The integration is modifying the traditional model of credit assessment, and now, in addition to a credit rating, a wide array of financial, operational, and behavioural data will be used to build an all-encompassing picture of a borrower's creditworthiness (Adebayo, 2025).

The digital finance case is one in which traditional structured data (balance sheets, income statements, past credit history, etc.) are combined with alternative and unstructured data (transactions, payment behaviour, supply chain relationships, social media posts, online reputation scores, and so on). Several types of data can be used to build a dynamic risk profile for an individual by collecting both their past behaviour in handling funds and their current living conditions; thus, it will be more precise and detailed in evaluating the risk of default (Misato, 2025).

An intelligent assessment model can be built using machine learning and deep learning to process a large amount of data for complex, high-volume problems in the ecosystem. These models show some faint patterns, non-linear relationships and new indications of risk that have gone unnoticed before. Indicatively, suspicious payment behaviour or a significant increase in the amount of transactions may be triggered to issue an automatic alert, take remedial measures promptly, and adjust the credit limit dynamically. These models have continuous learning processes that can adjust their risk profiles with new information and prevent the risk assessment from being out of date due to changes in market conditions or behaviour by borrowers (Avickson et al., 2024).

Digital finance also supports the automation, scaling and optimisation of risk assessment. Distributed Ledger Technology (DLT) and cloud computing can be used to improve the efficiency and reliability of the process for data collection, preprocessing and analysis by reducing manual intervention. In combination with intelligent models, a large number of assets can be managed in an organized manner by financial institutions, high-risk parties among them can be identified promptly, and appropriate data-driven decisions can be made regarding loans, credit releases, risk reduction, etc. Modern AI systems, such as ensemble and attention-based models, have improved predictive performance, handled high-dimensional data, and offered explainable results through SHAP and LIME; they also promote transparency and regulatory compliance (Samson-Onuorah, 2025).

Additively, new technologies such as large language models can be used to increase the efficiency of financial inclusion through high-accuracy credit rating and viability analysis of non-performing enterprises. Active credit portraits, real-time analysis and smart assessment technology can be used to build a robust, highly responsive credit evaluation system for digital finance to reduce the risk of default and promote the healthy development of businesses (Adebayo, 2025).

5 Problems in Enterprise Credit Portrait and Risk Assessment

Reinforcement Learning and Agent-based systems are relatively advanced AI models that have added new difficulties to enterprise credit risk assessment. Autonomous systems that affect

lending decisions should be used carefully to ensure that they are explainable, comply with regulations and fair in an ethical way (Rizinski and Trajanov, 2026). Although black-box models are relatively accurate, they have the problem of being unable to explain the reasoning behind credit decisions, and thus are not transparent, fair, and socially responsible. In addition, these models are relatively computationally intensive and require a substantial amount of high-quality, annotated data and technical skills. The above demands will be even more difficult for financial institutions in developing countries that are limited in terms of infrastructure, data availability and qualified staff. The unstable economic environment and rapid changes in the digital finance ecosystem are also creating new situations, so the research tools that need to be used are unlikely to be current long after they are published. To address these problems, scholars and practitioners have been using various types of hybrid models, such as CNN-XGBoost hybrids to extract features and predict based on historical financial and operational data, and attention-based CNN-BiLSTM hybrids to leverage previous financial and operational information. The goals of these hybrid systems are to trade off the accuracy of prediction for interpretability and practicability in operation (Chinnaraju, 2025), as shown in Figure 3.

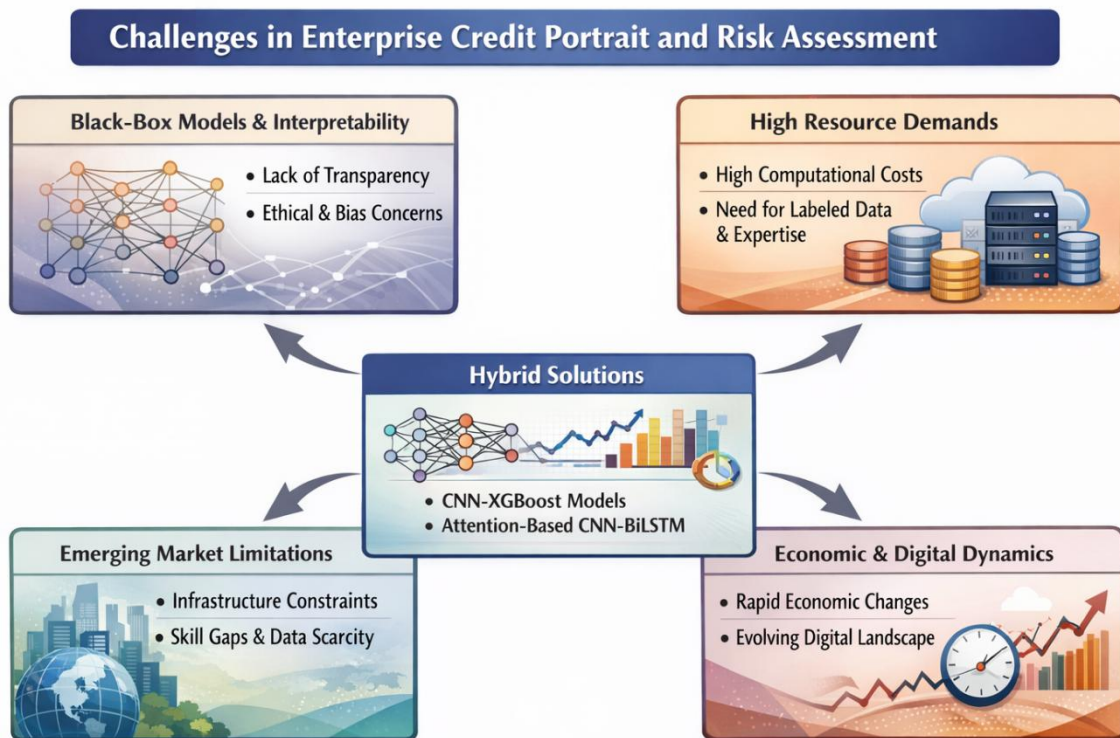


Figure 3: Main Problems in Enterprise Credit Portrait and Risk Assessment, including model interpretability, resource constraints, market limitations, and the role of hybrid AI solutions.

5.1 Data Quality and Availability

The first two problems of enterprise credit reports are accuracy and completeness of the data. Digital finance platforms generate a large amount of data, but this data is generally discrete and heterogeneous, coming from multiple sources such as financial statements, transaction records, supply chain data, social media discussions, other online reputation indicators, and so on (Song et al., 2021). Missing or irregularly spaced data and noise in the data may harm the performance of credit report and risk prediction models. Small and medium-sized enterprises in developing countries have not maintained their own financial records or other data in the past, and therefore it is difficult to conduct an all-round risk assessment now (Nahar et al., 2024).

Given that there is no data, a specific model will need to be employed for processing small-scale or unbalanced data. Synthetic data generation, transfer learning and conditional generative models can be used to augment the available data, and distributed ledger technology can enhance the security and traceability of the data. If the proportion of default is very small compared to non-default, then one can use oversampling or undersampling techniques, or a cost-sensitive approach to address the problem of class imbalance. Discontinuities in the financial data of the institution also make it difficult to apply more advanced methods, such as ensemble learning or GAN-based feature selection. In addition, due to the lack of specific behavioural and non-financial data, especially for small and medium-sized enterprises (SMEs), the impact of models aiming to build an all-encompassing view of enterprise creditworthiness has been restricted (Shi et al., 2025). SMEs have a default rate of around 5%-10%, so it is difficult to obtain a large number of samples for modelling. Therefore, some reasons for the strong data imputation and augmentation efforts in this team are to produce rich and reliable credit portraits.

5.2 Integration of Structured and Unstructured Data

One of the main problems in the assessment process of a company's credit is how to integrate the structured data (such as financial statements and transaction history) with unstructured data (such as emails, online behavior, social media sentiment and textual reports). There are various problems of technicality due to different data forms, scales and quality. Properly extract features, normalise the data and perform other transformations so that all the information is captured without bias or errors (Borrohou et al., 2024).

Unstructured data may require Natural Language Processing (NLP) and sentiment analysis, etc., and structured data generally uses traditional quantitative analysis. Constant collection of new information can help to quickly know how the economic environment and thus credit risks have changed; otherwise, at the pace of market changes now, only a large-scale historical collection process can be used. Therefore, a high-capacity data-fusion structure for multi-modal data needs to be constructed. The above structures should be able to integrate financial indicators, narrative reports, behaviour changes and transaction history to construct an all-encompassing and flexible profile of an enterprise's credit risk. SMEs often have reduced financial transparency, and thus multimodality of data can be used to compensate for the lack of specific financial indicators and enhance the construction of risk and resilience (Borrohou et al., 2024).

5.3 Model Complexity and Interpretability

High-performing machine learning and deep learning models, such as neural networks, random forests, gradient boosting and ensembles, have excellent predictive capabilities but are also difficult to interpret. Black-box models are less interpretable, and thus difficult to determine the reasons why a financial institution or regulator has labelled a specific enterprise as high-risk. A failure to disseminate may result in low trust among all parties and thus fail to regulate or be misguidedly managed (Oyasiji et al., 2023).

In order to address the above problems, explanation methods for AI models are being used to present some interpretability of the model's predictions. However, the above methods are likely to increase the computational cost and require special knowledge. Continually monitor the risks of credit and, at the same time, use interpretable models to ensure that AI-driven decisions are auditable and subject to accountability. Deep learning models have shown limited interpretability in assessing the credit risk of small and medium-sized enterprises (SMEs), and regulators are increasingly paying attention to issues of fairness, equity and bias in automated lending decisions (Yu et al., 2024). Add network data to the existing data, identify connections

and contagion effects among connected enterprises, enhance the accuracy and interpretability of the model, and help institutions understand systemic risk more clearly for better-informed lending decisions (Wang et al., 2025).

5.4 Dynamic and Changing Market Environment

The enterprise's risk profile changes constantly due to fluctuations in the economy and market volatility, changes in operations and altered behaviour of borrowers, etc. Traditional fixed models are unable to handle these fluctuations, so the prediction accuracy of intelligent models needs to be continuously improved through retraining and optimisation. A flexible risk evaluation is to be performed in the construction of an adaptive learning system, which can shift the parameters of a model flexibly according to new data (Bello et al., 2024).

To help the adaptive system adjust when there is a change in the concept, a new model will be used. In light of new changes in the economy and industrial structure, some new forms of credit risk have arisen recently that have not been included in the previous risk assessments. Given that the sectors of agriculture and manufacturing SMEs have a longer production cycle and are more exposed to changes in nature and the market, active adjustment is needed for these sectors. The above dynamic models are demanding in terms of computing power, data pipelines and other facilities, so a high-quality one needs to be established for continuous and reliable risk monitoring (Latief and Hamilton, 2024).

5.5 Security and Privacy Concerns

The content of the credit assessment will contain sensitive financial and business data; therefore, it needs to be secure and private. Violations, hacks and other unauthorised accesses to information may cause a loss of trust and other harm. Strengthen the encryption and security of enterprise data storage, improve access control and data management.

Advanced Privacy-Preserving Techniques, such as homomorphic encryption and federated learning, can be employed to train models jointly in multiple organisations without sharing raw data. The above ways can be used to enhance the predictive models of all parties cooperatively without violating any privacy. However, these measures have a relatively high computational overhead and architectural complexity; thus, they are more costly in terms of infrastructure investment and technical personnel for small and medium-sized non-bank financial institutions. Privacy, security and interpretability in the real-time processing of high-frequency dynamic data are the main problems for credit risk assessment at large enterprises today (Baradaran, 2025).

5.6 Regulatory Compliance and Ethical Considerations

AI-driven alternative data-based credit assessment methods need to comply with regulations and ethics in order to be used. Regulations for credit are open access, non-discrimination, fairness and accountability. High-dimensional, complex and adaptive AI models may be less compliant, especially when the models change dynamically or when they are trained on irregular data sources (Samson-Onuorah, 2025).

The requirements for audits and compliance need to achieve a certain level of both prediction accuracy and interpretability. Regularly carry out audits to prevent bias and ensure that the results are consistent with those from other areas; thus, maintain the public's and regulators' trust. Explainable AI technology can be employed to address the above problems by providing explanations for credit decisions and ensuring fairness in the operation of AI systems in the highly regulated field of finance (Anang et al., 2024).

5.7 Resource and Expertise Requirements

The technological infrastructure, specific software and qualified personnel for enterprise credit portrayal and intelligent risk assessment systems are all relatively high-cost. Data science, machine learning, finance, cybersecurity and regulatory compliance expertise are all needed (Ma, 2025). Smaller institutions or start-ups have limited resources and are therefore unable to implement the new model.

External vendor mode may also result in the above problems: loss of data independence, difficulties in model verification, and vendor risk management issues. There are no regulatory sandboxes or pilot programs for the new model at present. It is difficult to achieve both high accuracy and interpretability simultaneously for model-aid in regulatory supervision of complex "black box" models, such as deep neural networks. Explainable systems, such as SHAP and LIME, are increasingly needed to provide the institution with actionable information without affecting prediction accuracy, and at the same time, they should not be overly complex or burdensome for regulation (Abe, 2025).

6 Future Directions and Research Opportunities

With changes in the surrounding environment of enterprise credit assessment, new opportunities for innovation have gradually emerged due to the development of artificial intelligence (AI), big data analysis, blockchain technology, continuously learning systems, etc. As the world of financial ecosystems will continue to be more digitalised and interconnected, research and development in these directions are necessary to improve the accuracy, flexibility and transparency of credit risk assessment (Avickson et al., 2024).

6.1 Emerging AI and Big Data Techniques

Discussing the future development and applications of new AI and Big Data technology in enterprise credit risk assessment. New AI technologies such as deep reinforcement learning, graph neural networks and hybrid ensemble models are more suitable for prediction because they can learn complex non-linear relationships in both structured and unstructured data. The above ways can show some changes in a company's behaviour, operating conditions and financial indicators that have not been revealed by the traditional statistical tests (Hezam et al., 2025).

Big Data Analytics also provides more data for the training of Artificial Intelligence through high-frequency, large-volume data released by digital finance platforms. These data sets are transactional records, supply chain links, consumer feedback and other market data. AI and Big Data are used to build an all-weather, high-frequency credit assessment model and enhance risk control. Future studies will aim to develop more interpretable AI models that can understand the complex patterns in a large number of data and thus ensure that the advantages of predictive AI are not obtained at the expense of regulatory transparency and ethical fairness (Minh et al., 2022).

6.2 Integration with Blockchain and Decentralised Finance

Decentralised Finance (DeFi) and Blockchain Can Help Enhance Enterprise Credit Ratings. A blockchain is used to build an unalterable record of the data, and it is open, transparent and impervious to tampering; thus, previous issues with data reliability, fraud and reconciliation among financial institutions have been addressed. A decentralized ledger that can securely record financial transaction data and supply chain information, as well as payment histories,

will be used by the credit assessment system to access verified and tamper-proof data to improve both the trust and accuracy of the system (Ahmed, 2025).

Artificial intelligence (AI) risk models can be used with the blockchain platform to automatically evaluate the credit risk of a loan and take timely counterparty measures; at the same time, data privacy and security will be protected. Smart contracts can autonomously realize the credit agreement to lower operating and transaction costs. DeFi apps are also likely to promote the financial inclusion of the unbanked by providing credit for these businesses and using advanced risk models for fundraising. The next research directions will include studies on the convergence of AI, blockchain and distributed ledger technologies in the context of future hybrid architectures to enhance the scalability, security and regulatory compliance of decentralized credit assessment systems (Bhumichai et al., 2024).

6.3 Continuous Learning Systems and Improvements in Predictive Analytics

The first is to build a system of continuous learning that can adapt to the changes in the market and the new business models of enterprises at any time. Static model are not in line with the requirements of streaming data that need continuous updating for real-time predictions. Allow early identification of risks, serve as an early warning system, and take timely credit measures (Lin, 2022).

Online learning, reinforcement learning and adaptive ensemble models are among the methods for making predictive analytics self-optimising in response to new patterns. For example, any changes in behaviour of transactions, market fluctuations or supply chain disruptions will be shown in these models and promptly and accurately used to update credit assessment information. In addition to the above, a continuous learning system can conduct scenario analysis, stress tests and risk simulations of a system under different economic conditions to provide institutions with practical information for portfolio management (Majka, 2024).

In the future, some studies will add issues such as concept drift, overfitting, model instability, etc., and improve the strength and reliability of these adaptive models. Multimodal Data can also be added to boost the predictive power of the model, including text, images, behaviour and so on. The new system will also be a continuous learning model that is explainable; it can make decisions in real time under current regulations and be easier to understand (Baradaran, 2025).

7 Conclusion

Mining enterprises' credit portraits and intelligent methods for default risk assessment are now typical ways to assess the credit risks of enterprises in the new digital finance system. Credit portraits are built from structured and unstructured data, other financial indicators, and machine learning to show a full-process view of a company's financial and operating health, as well as behaviour. The above multi-dimensional profiles will help the financial industry move away from the old way of thinking and evaluation; a real-time monitoring mechanism of all stages of the process will be established, potential default situations can be foreseen in advance, and more precise loan decisions will be made. Intelligent risk assessment models that have achieved good results in practice are mainly classified as supervised and unsupervised learning, ensemble models, deep learning architectures, etc., but their applicability to high-dimensional and complex enterprise data is still limited. The above models are combinations of digital finance platforms that can be scaled, learn and adapt to risks continuously, and enhance the efficiency and robustness of credit assessment.

However, this will still be accompanied by problems such as data quality, readability, a changing market environment, regulatory pressures and resource constraints, so the full effect of these advanced methods will not be realised. New technologies can be employed to address the above problems, and by means of blockchain, federated learning and hybrid AI models, the openness, security and accessibility of enterprise credit assessment will be further strengthened. Finally, through the application of enterprise credit portrait mining and intelligent risk assessment technology in digital finance, a new model of proactive, precise and fair credit examination has been established. The above combined solution will reduce the risk of default, promote healthy development, and support the expansion of financial inclusion and innovation in enterprise finance to build a stable and responsive system of credit management for digitally advanced areas.

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Yueling Hua was born in Baoding, Hebei, China, in 2002. She obtained a bachelor's degree from Shijiazhuang Tiedao University in China. She is currently studying at the School of Business, Jiangnan University. Her main research direction is corporate finance and capital markets.

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