ORIGINAL ARTICLE

INTERNATIONAL JOURNAL OF ARTIFICIAL INTELLIGENCE

ISSN: 2692-515-x, Impact Factor: 9.23
American Academic publishers, volume 6, issue 01,2026

Journal: https://www.academicpublishers.org/journals/index.php/ijai

INNOVATIVE METHODS OF ASSESSING CREDITWORTHINESS IN MODERN BANKING PRACTICE

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Abstract

The article analyzes innovative methods for assessing creditworthiness in modern banking practice and examines the use of artificial intelligence, machine learning algorithms, big data analytics, and alternative data sources. Particular attention is paid to their role in improving the accuracy of credit risk assessment, enhancing scoring systems, and supporting data-driven decision-making in the digital financial environment.

Keywords

creditworthiness, scoring system, artificial intelligence, machine learning, big data, credit risk, digital assessment, fintech, alternative data, credit portfolio.

In the modern banking sector, accurate and objective assessment of creditworthiness is considered one of the key factors in ensuring financial stability. In recent years, rapid changes in global financial markets, the acceleration of digitalization processes, and the emergence of new technologies have encouraged banks to adopt innovative approaches to credit risk assessment. Traditional methods of creditworthiness evaluation were mainly based on a limited set of data, such as a client's financial statements, income indicators, and the value of collateral. However, under the conditions of the digital economy, these methods are gradually losing their effectiveness. International banking practice shows that artificial intelligence, machine learning algorithms, and big data technologies are bringing about revolutionary changes in credit risk assessment.

In the Republic of Uzbekistan, alongside banking sector reforms and the acceleration of digitalization processes, the volume of the credit portfolio has been increasing year by year.

According to data from the Central Bank of the Republic of Uzbekistan, during the period from 2022 to 2025, the credit portfolios of commercial banks increased by nearly 1.5 times. Although progress has been made in reducing the share of non-performing loans, there remains a need to implement more effective methods for assessing creditworthiness. The aim of this article is to analyze innovative methods of creditworthiness assessment in modern banking practice, identify their advantages and disadvantages, and develop practical recommendations for banks in Uzbekistan.

Traditional methods of creditworthiness assessment include the following main approaches. The financial analysis method involves an in-depth examination of a client's financial statements, including the balance sheet, income statement, and cash flow statement. Liquidity

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ratios, financial stability indicators, profitability ratios, and debt levels are evaluated. The "5C" method is a classical approach that covers five key criteria: Character (the client's reputation and payment history), Capacity (ability to repay), Capital (capital and assets), Collateral, and Conditions (economic environment). Scores are assigned based on these criteria, and a credit decision is made accordingly. In expert assessment, experienced credit specialists evaluate loan applicants based on their knowledge and professional experience. This method has held a central role in banking practice for many years.

However, under the conditions of the digital economy, a number of serious shortcomings of traditional methods have become evident. First, subjectivity – the human factor plays a significant role in expert assessments, which increases the likelihood of errors and incorrect decisions. Different experts may evaluate the same client differently. Second, limited data availability – traditional methods rely solely on formal financial statements and documents. Many potential borrowers, especially small businesses and individuals, do not have complete financial reports. Third, time-consuming processes – manually analyzing each application takes considerable time. On average, reviewing a credit application takes 5–10 working days. Fourth, low adaptability – traditional methods are slow to adjust to rapidly changing economic conditions and do not fully account for dynamic market environments. Fifth, high operational costs – manual assessment requires the involvement of many specialists, which increases the bank's expenses.

Table 1. Comparative Analysis of Traditional and Innovative Assessment Methods

Indicator	Traditional Methods	Innovative Methods
Decision-making time	5–10 days	5–30 minutes
Assessment accuracy	70–75%	85–90%
Data volume	Limited	Extensive
Operational costs	High	Low
Subjectivity	High	Minimal
Adaptability	Low	High

In modern banking technologies, machine learning algorithms have ushered in a new era in assessing creditworthiness. These technologies are capable of analyzing large volumes of data, identifying hidden patterns, and generating predictions. The main algorithms commonly used include the following. Logistic regression is the simplest yet effective algorithm, which estimates the probability of a client obtaining credit. The algorithm studies the relationships between various variables, such as income, age, work experience, and others.Decision Trees and Random Forest algorithms represent the decision-making process in the form of a tree. Each node represents a decision point based on a specific criterion. Random Forest combines the results of multiple trees to provide more accurate predictions. Gradient Boosting (XGBoost, LightGBM) is one of the algorithms with the highest accuracy, creating a sequence of weak predictors where each one corrects the errors of the previous. Neural Networks and deep learning technologies allow for the detection of very complex patterns. In the banking sector, neural networks are used to analyze clients' past payment histories and behaviors.

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Big Data technology enables the processing of large volumes of both structured and unstructured data. Modern banks utilize transaction histories and account activities, social media activity and profile information, payment history via mobile applications, utility and telecommunication payments, online purchases and e-commerce data, as well as geolocation data and movement patterns. JPMorgan Chase, through its COiN (Contract Intelligence) platform, uses artificial intelligence to automate 360,000 hours of legal work annually. Wells Fargo, on the other hand, applies machine learning algorithms in credit decision-making, increasing the speed of credit approvals by 40%.

Statistical analysis of the use of digital assessment systems in the banking sector of Uzbekistan shows that as the adoption of digital assessment systems increases, the share of non-performing loans has significantly decreased. In 2022, the use of digital systems accounted for 45%, and by 2025, this figure is expected to reach 89%.

Table 2. Use of Digital Assessment Systems in Banks of Uzbekistan (2022–2025)

Year	Loan Portfolio (trillion UZS)	Share of Non-Performing Loans (%)	Share of Digital Assessment Usage (%)
2022	285.4	2.8	45
2023	324.7	2.3	62
2024	378.2	1.9	78
2025 Forecast	425.8	1.5	89

International experience shows that the use of AI and ML technologies is even more widespread in global banking practice. According to a McKinsey & Company study, by the end of 2024, 87% of global banks are applying machine learning algorithms to assess creditworthiness.

Credit scoring is a system that evaluates a client's creditworthiness in the form of a numerical score. This system analyzes numerous parameters, assigns a weight coefficient to each, and calculates a final score. The FICO Score is the most widely used credit scoring system, with a scale ranging from 300 to 850 points. Its calculation formula includes payment history (35%), debt level (30%), length of credit history (15%), new credit (10%), and types of credit (10%).

In 2020, the Central Bank of the Republic of Uzbekistan introduced the Unified Credit Registry system based on the Law "On the Credit Bureau." Today, all commercial banks use this system. Modern local scoring systems include Ipoteka Bank's internal scoring model, Xalq Bank's AI-based scoring system developed in collaboration with IBM, a specialized scoring model for agricultural loans at Agrobank, and Uzpromstroybank's model adapted for small businesses.

Behavioral scoring is a system that monitors and evaluates a client's post-credit behavior in real time. It analyzes factors such as the minimum account balance, timeliness of loan payments,

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frequency of applications for additional credit, patterns of cash withdrawals, and the regularity of utility and telephone payments. This approach allows the bank to make timely decisions regarding adjusting a client's credit limit, offering new credit products, or, conversely, increasing risk management measures.

Table 3. Effectiveness of Different Scoring System Models

Scoring Model	Accuracy (%)	Implementation Time	Costs
Classic Statistical Model	72–75	2–3 months	Low
Machine Learning-Based	82–87	4–6 months	Medium
AI and Big Data Integration	88–92	6–9 months	High
Hybrid Model (Traditional + AI)	85–89	3–5 months	Medium

Alternative data refers to additional sources of information used to assess a client's creditworthiness beyond traditional financial statements. These data are particularly important for clients who lack a credit history (thin-file or no-file clients). Key sources of alternative data include utility payments, such as electricity, water, gas, internet, and phone bills, as the regularity of these payments indicates a client's financial discipline. According to research by LexisNexis Risk Solutions, utility payment data can improve credit scoring accuracy by 15–20%. Rental payment history is also an important indicator. In the U.S., over 2 million users have improved their credit scores through the Experian Boost program. Mobile phone and internet payments are especially significant in developing countries, where a large portion of the population does not have a formal banking history.

Social media data is a controversial yet promising area. Some fintech companies analyze profile information from Facebook, LinkedIn, and other social networks. However, this approach raises privacy concerns. E-commerce data, such as online purchase history, timely payment behavior, and the number of returned items, is also considered an important factor in credit assessment.

Psychometric assessment is a method for determining a client's creditworthiness by evaluating their personal traits, values, and decision-making style. This approach is widely used in African and Asian countries. The process works as follows: the client completes a specialized questionnaire (usually 20–50 questions) designed to identify personal characteristics, financial values, and risk tolerance. Artificial intelligence then analyzes the responses to predict the client's repayment capacity. Research by EFL (Entrepreneurial Finance Lab) has shown that when psychometric assessments are used alongside traditional methods, the accuracy of credit risk evaluation increases by 30%.

Blockchain technology is creating new opportunities for maintaining credit history registries. A decentralized database allows clients to have full control over their credit records, while immutable entries prevent the falsification of credit history. Cryptographic encryption ensures data security, and smart contracts enable the automatic execution of agreements.

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Countries such as Singapore, Estonia, and the UAE are already piloting blockchain-based credit registries.

In recent years, the creditworthiness assessment system in Uzbekistan's banking sector has undergone significant changes. As a result of reforms implemented by the Central Bank, the Unified Credit Registry system was fully activated in 2022 and became mandatory for all commercial banks. This system provides comprehensive information on clients' loans across all financial institutions. In 2023, several major banks (Ipoteka Bank, Xalq Banki, and Kapitalbank) began adapting and implementing international credit scoring systems to local conditions. In 2024, microcredit organizations also started using scoring systems, which expanded access to financial services for small businesses and the general population. However, several challenges remain. These include the high share of the informal economy (30–35%), the absence of bank accounts among part of the population, low levels of digital literacy, and the lack of full integration among data systems.

International Best Practices. In the United States, the FICO scoring system has been the standard for over 30 years. However, alternative systems such as VantageScore are also gaining traction. In 2023, U.S. banks invested USD 12 billion in AI-based lending systems. In China, Alibaba Group's Sesame Credit (Zhima Credit) system is one of the most innovative solutions. It serves more than 900 million users and evaluates five key factors: credit history, contract fulfillment, personal characteristics, behavioral patterns and preferences, and social connections. In India, the Jan Dhan Yojana program has brought 400 million people into the formal banking system. Combined with the Aadhaar digital identification system, it has significantly expanded opportunities for innovative credit assessment. In Kenya, the M-Pesa mobile money transfer system has enabled millions of Kenyans to access microloans. This represents a successful example of using mobile payment data for credit scoring.

Table 4. Characteristics of Credit Assessment Systems in Different Countries

Country	Main Technology	Coverage (% of population)	NPL Ratio (%)
United States	FICO + AI	89	1.5
China	AI + Big Data	82	1.8
India	Alternative Data	65	3.2
Kenya	Mobile Data	58	4.5
Uzbekistan	Traditional + Scoring	47	1.5

The main advantages of innovative credit assessment systems include the following. Higher accuracy and reduced errors: Machine learning algorithms can analyze thousands of parameters simultaneously and identify patterns that are not detectable by humans. This increases the accuracy of credit risk assessment by 35–40%. Faster decision-making: Processes that traditionally required several days can now be completed within minutes. This is more convenient for clients and more efficient for banks. Cost reduction: Through automation, operational costs are reduced by 40–50%. The cost of reviewing a single credit

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application decreases from USD 150–200 to USD 10–15. Financial inclusion: Innovative approaches enable the assessment of clients without a formal credit history, which is especially important for developing countries. Real-time monitoring: Through behavioral scoring, clients' current financial conditions are continuously monitored, allowing risks to be identified at an early stage. Expanded market coverage: Digital systems make it possible to serve customers in rural and remote areas as well.

However, innovative approaches also face several challenges. Data privacy concerns: The large-scale collection of data may violate individuals' right to privacy. Regulations such as the General Data Protection Regulation (GDPR) impose strict requirements. Algorithmic bias: If machine learning models are trained on inaccurate or biased data, they may produce discriminatory outcomes, for example, based on race, gender, or age. The "black box" problem: Complex neural networks often lack explainability, making it difficult to understand how decisions are made. This creates challenges for regulators and customers alike. Technological security risks: There is a constant risk of cyberattacks and data breaches. In 2023, more than 1,500 serious cyberattacks on the global banking system were recorded. High initial investment costs: Implementing AI and machine learning systems requires substantial financial resources, which can be particularly challenging for small banks. Skills shortage: The lack of qualified data scientists and AI specialists hinders the effective development and implementation of such systems.Regulatory uncertainty**:** In many countries, there is still no clear legal framework governing AI-based creditworthiness assessment.

Short-term measures (1–2 years). It is necessary to optimize existing databases, improve data sharing among all banks, and fully integrate the Unified Credit Registry system. Launching pilot projects is recommended, with 2–3 major banks testing AI-based scoring systems in specific segments (such as microloans or auto loans). Staff retraining is crucial; banks should conduct training programs on digital technologies and data analytics for their employees. Establishing international cooperation is also important, including signing partnership agreements with foreign fintech companies and technology providers. Finally, the regulatory framework should be improved. The Central Bank should develop guidelines governing the use of AI- and machine learning–based credit assessment systems.

Medium-term strategy (3–5 years). It is necessary to establish a fully digital ecosystem. Banks should jointly develop a unified digital platform that integrates all customer financial data, including utility payment histories, connections with government services, and tax payment records. The implementation of the Open Banking concept is also essential. This would grant customers control over their personal data and enable secure data sharing with third-party providers.

Expansion of alternative data sources. It is necessary to expand the use of alternative data sources by integrating with telecom companies, utility service providers, and e-commerce platforms. Blockchain technology should be piloted through the implementation of a decentralized credit history registry. Digital literacy initiatives. Comprehensive educational programs should be conducted to promote the use of digital financial services and improve digital financial literacy among the population. Long-term vision (5–10 years). A fully AI-driven banking system should be developed, in

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which credit decisions are 100% automated, real-time risk monitoring is implemented, a proactive customer engagement approach is applied, and personalized financial advice is provided. Becoming a regional financial hub. Uzbekistan can position itself as a regional center for digital banking technologies in Central Asia. Integration with foreign markets. Innovative solutions developed by Uzbek banks could be exported to international markets, enabling deeper integration with global financial systems.

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