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A COMPARATIVE STUDY OF TRADITIONAL AND AI-POWERED MODELS FOR EVALUATION OF CREDITWORTHINESS [24]

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Abstract: *Due to the weak development of the financial market in Bulgaria, most companies finance their investments with bank loans. The households also use bank loans to purchase durable goods. The individuals balance their cash inflows and outflows through bank loans. This requires the bank to assess on each loan request the likelihood that a customer or firm will meet its obligations, which is essential for the stability of the financial system and for minimizing losses from non-performing loans. The creditworthiness assessment is a key component in credit risk management and financial decision making by both banks and other lending institutions.*
Traditional models for evaluation of creditworthiness are a solid foundation and are still widely used today - especially in more conservative lending institutions. With the growth of data, technology and demands for greater accuracy, new techniques (machine learning, AI) are also emerging - but this does not refuse traditional approaches, but rather complements them. For borrower assessment, it is important to combine both financial/balance sheet information and qualitative aspects (governance, business environment, guarantees)- which the traditional approach does, albeit with limitations. By the integrated mechanism has a balance between accuracy, speed and confidence in the decision-making process.
Keywords: *Banks, credits,* creditworthiness*, AI models*

INTRODUCTION

Due to the weak development of the financial market in Bulgaria, most companies finance their investments with bank loans. The households also use bank loans to purchase durable goods. The individuals balance their cash inflows and outflows through bank loans. This requires the bank to assess on each loan request the likelihood that a customer or firm will meet its obligations, which is essential for the stability of the financial system and for minimizing losses from non-performing loans. The creditworthiness assessment is a key component in credit risk management and financial decision making by both banks and other lending institutions.

For decades, traditional models for evaluation of creditworthiness based on statistical models such as financial ratio estimation, logistic regression and discriminant analysis have dominated the practice. They are characterised by a high degree of transparency and interpretability, which makes them preferred in highly regulated environments. However, these approaches often have a limited ability to capture complex relationships and process large volumes of diverse data.

With the advancement of technology and the penetration of artificial intelligence in finance, there is an increasing focus on AI-based models. These AI-based approaches offer higher predictive accuracy, the ability to use alternative data sources (such as behavioural and non-financial indicators) and better adaptability to changing market conditions. However, they have limitations related to explainability, ethical use of data and regulatory compliance.

This study aims to provide a comparative analysis between traditional and AI-based credit scoring models, focusing on their characteristics, advantages, disadvantages and applicability.

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EXPOSITION

Literature Review

As early as the 1960s, Altman (1968) used discriminant analysis and constructed one of the first widely known models to predict firm bankruptcy using financial ratios (debt, current assets, earnings, etc.). Louzada et al. (2016) in "Classification methods applied to credit scoring: A systematic review and overall comparison" review a wide range of publications in the field, identifying which techniques are most used and how paradigms are shifting in credit scoring. Rogojan et al. (2023) also review both traditional and modern (machine learning) models - a good indicator of how they are evolving. Abdou & Pointon (2011) analyze a variety of techniques - statistical, econometric, etc. - and conditions for successful scoring.

In their comparative study, Smith & Johnson (2020) highlight that AI-driven techniques in credit scoring models significantly improve prediction accuracy compared to traditional methods. They note improvements in risk assessment accuracy and the ability to handle complex data interactions. C. Onay & E. Öztürk (2018) focus on how big data" and alternative sources are changing the estimation of the credit query. Leonardo Gambacorta, Fabiana Sabatini & Stefano Schiaffi (2025) work with real data from the banking sector and look at the interaction between AI and traditional relationship banking ("relationship lending").

The advent of artificial intelligence (AI) and machine learning has brought about a fundamental shift in multiple fields, including finance (Gautam & Mittal, 2022). AI-driven techniques, such as decision trees, neural networks, and ensemble methods, provide improved capabilities to analyze large volumes of data, uncover hidden patterns, and generate more accurate predictions (Jora et al., 2022; Soori, Arezoo, & Dastres, 2023). These advanced approaches demonstrate the potential to increase the accuracy and reliability of credit rating models while addressing the limitations of conventional ones. Podell (2024) highlights the impact of AI-driven techniques on reducing costs and efficiency in credit scoring processes. Their research demonstrates that automation and optimization through artificial intelligence leads to streamlined operations and cost reduction.

Traditional models are a solid foundation and are still widely used today - especially in more conservative lending institutions. As data, technology and demands for greater accuracy grow, new techniques (machine learning, AI) are emerging - but this does not invalidate traditional approaches, rather it complements them. The limitations of traditional models (related to lack of history, lack of data) are well documented. For borrower assessment, it is important to combine both financial/balance sheet information and qualitative aspects (governance, business environment, guarantees) - which the traditional approach does, works with limitations. The literature highlights that for smaller firms or those with non-standard histories, traditional models may not be sufficient - and that new data or methodologies need to be added.

Characteristics of a traditional credit scoring model

It is used primarily for individuals and firms with access to credit history. The data is primarily "historical" (how the applicant has done to date) and from traditional sources (credit report, available loans, loan payments, report o receivables and expenses, balance sheet, etc.) It is based on a set of well-known and measurable indicators.

In the traditional creditworthiness assessment model, the lender (bank, leasing/factoring company, etc.) looks at the applicant company with a set of "standard" criteria:

Financial position: balance sheet, income statements, cash flow, profitability, liquidity, debt/equity ratios, current assets/current liabilities.

- Payment history: whether the company has met its current obligations, whether it has defaulted, what its credit history has been, what collateral it has provided.
- Business model, activity and market environment: what is the business like - is it stable, what are the risks, what are the customers and suppliers, what is the competition.
- Owners/management: reputation, experience, management capacity, legal and fiscal history.
- Collateral and guarantees: existence of mortgages, pledges, guarantees, other assets that can serve as recourse. In addition, an assessment of the terms of the loan: term, currency, interest rate, payment structure, and how the firm will be able to cope in adverse scenarios.

- In principle, the lender may request additional data and apply stress tests (e.g. how the firm would cope with higher interest rates, a drop in sales, etc.).

The sequence of the evaluation is as follows

- Collection of financial statements for the last 2 3 years + current data.
- Calculation of key ratios (liquidity, profitability, debt/equity, working capital, etc.).
- Business environment and risk analysis (industry, competition, customer and supplier dependencies).
- Verification of payment history - whether the company has been in arrears, whether there are arrears, what are the terms.
- Assessment of governance, ownership and legal framework - is it transparent, are there any litigation, related parties, etc.
- Lending decision: based on risk assessment and repayment capacity, limit, term, conditions, possible collateral are determined.

Advantages of the traditional method:

- Structured and familiar process.
- This model is time-tested, standardized and well understood (although the exact formula is often a trade secret).
- Good predictive power for accounts with rich credit history and good transparency.
- For the lender, an easier decision to justify.
- Easier to justify to regulators and internal audits.

Disadvantages of traditional model:

- People and companies with short or no credit history ("thin file", "credit invisible") are often excluded from assessment or receive unfavourable terms.
- The model is often based on past behaviour and may not capture new changes in income, market environment or credit ("lagging indicators").
- Limited in terms of innovation: do not always include non-traditional data, are not always adaptive.
- Can be slower and more labor-intensive to process (manual analysis, lots of documentation).
- Sometimes lack of transparency for the final candidate on how exactly the score is formed.

Characteristics of an AI-based credit scoring model

AI-based credit scoring models are algorithms that use machine learning (ML), deep learning (DL), and big data processing to predict the likelihood that a customer or company will meet its financial obligations. The goal is to make more accurate, rapid and personalized credit assessments using multiple and often non-traditional data sources.

Table 1 Main types of AI models

Logistic regression (with ML tuning)	**A more advanced version of classical logistic regression**	**Interpretable, benchmarkable**
Decision Trees	Classifies using hierarchical "rules"	Easy to interpret, but can be unstable
Random Forest	Combination of multiple decision trees	Good balance between accuracy and stability
Gradient Boosting (XGBoost, LightGBM, CatBoost)	Complex sequence of models trained one after another	Very high accuracy, popular in banks
Support Vector Machines (SVM)	Boundaries between classes in multidimensional space	Good on structured data, non-interpretable

Neural Networks (Deep Learning)	Network of layers that "learn" complex dependencies	High accuracy, hard to explain ("black box")
Bayesian Networks	Predictions based on probabilistic dependencies	Suitable for uncertain and incomplete data
Auto ML platforms	Automated model selection and optimization	Convenience but limited control

Source: Authors

Data used by AI models

- Traditional structured data:

Company financial statements (revenue, profit, liabilities, capital)
Banking history (loans, payments, limits, delinquencies)
Business history and registration

- Alternative/behavioural data:

Real-time transactional data - turnover, payments to suppliers, changes in flows
Fintech data - mobile payments, POS systems, e-invoices

Advantages of AI models

Table 2 Advantages of AI models

Automatic learning	**Models are trained on historical data and adapt over time**
Detecting hidden dependencies	AI finds relationships not seen in manual analytics
Using large and diverse data sources	Includes non-standard indicators, e.g. app behaviour
Fast query processing	Can estimate in seconds, even for large volumes
Adaptability to change	Models can be updated with new data, increasing their accuracy
Risk segmentation	AI can identify different types of customers/companies and group them by risk profile

Source: Authors

Disadvantages of AI models

Table 3 Disadvantages of AI models

Black box	**Difficult to explain why the model made a particular decision - problem with regulatory scrutiny**
Data dependency	If data is inaccurate, incomplete or biased, the model will learn incorrectly
Bias	Historical data can reproduce discrimination by gender, age, location, etc
GDPR and ethics	AI models must adhere to privacy, transparency and explainability requirements
Overfitting	The model "learns by rote" the data and doesn't do well with new examples

Source: Authors

Example structure of an AI-based credit rating model - stages

- Data collection - Financial and non-financial, Current and historical transactions.
- Data pre-processing - Cleaning, normalization, coding, noise removal.
- Feature extraction (feature engineering) - Create new indicators (e.g. seasonal earnings volatility).
- Model training - Algorithm selection (XGBoost, NN, Random Forest), Training with test and validation sets.
- Performance evaluation - Metrics: Gini, accuracy, F1-score, precision/recall.

- Integration and automation - Implementation in the bank's system or platform.
- Monitoring and updating - Detecting "model drift", adapting to market changes.

Applicability to companies in creditworthiness assessment

- Company without long financial history AI can use current transaction and behavioural data for assessment.
- Micro and small enterprises (SMEs). Alternative data (POS, fiscal cash registers, e-invoices) can replace the lack of traditional reports.
- Companies in a dynamic sector (e.g. IT, e-commerce). Model captures trends that traditional analysis misses.
- Need for speed and automation. Decisions can be made within minutes, without manual intervention

Comparative analysis of the traditional and AI - powered creditworthiness assessment models

Table 4 Comparative analyse

Criterio	Traditional scoring	AI-based scoring
Typical data	Credit report, payment history, debt, credit applications.	Usual credit data + alternative (e.g. mobile transactions, bills, behavior).
Methodology	Statistical models, formulas, fixed coefficients.	Machine learning, ensembles, dynamic models.
Estimation speed	In some cases slower, with manual intervention.	Rapid
Approach to "thin" profiles	Limited - many remain unaccounted.	Better - includes alternative data and can assess people with little credit history.
Transparency and explainability	Clearly differentiated factors, but formula is often a trade secret.	Can be "black box", requires extra effort to explain credit scoring models.
Approach to behaviour change	Less adaptive, often based on past history.	Adaptive, learns from new data, can change assessment quickly.
Risk of bias/inequity	Problems with "thin" profiles and disengagement.	Possible algorithmic bias if data is incorrect or incomplete.
Operational costs	Higher if involves manual checks and paperwork.	Lower with automated system, but requires investment in modelling and maintenance.
Regulatory/ethical aspects	Established practices but can be criticized for lack of innovation	New challenges: explainability, data protection, fairness.

Example scenarios for creditworthiness assessment

- If you have a rich credit history, stable income and traditional profile, traditional assessment is probably sufficient.
- If you are new to the credit system (e.g. student, young person, freelancer), or have an unstable income - AI-based scoring may give you a chance you wouldn't otherwise have.
- For lenders: moving to AI requires effort - qualitative data, models, controls and explain ability - but the potential is significant.
- For regulation: it is important to ensure that AI models do not discriminate, are transparent and subject to data protection requirements.

CONCLUSION

The development of credit scoring reflects the overall evolution in the financial sector from simple, interpretable and stable models to more flexible, dynamic and technologically advanced solutions. The traditional credit scoring models, such as logistic regression and financial ratio analysis, continue to be widely used due to their transparency, ease of implementation and compliance with regulatory requirements. However, they have serious limitations when dealing with large volumes of data, non-standardised information and new economic conditions.

On the other hand, AI-based models - including machine learning and deep neural networks - offer higher predictive accuracy, the ability to process a wide variety of data and the ability to automatically adapt to new patterns of behaviour. However, they are often more difficult to interpret and raise issues of ethics, transparency and fairness.

Benchmarking shows that the most effective approach is often a combined one - using AI models with integrated explainability mechanisms complemented by classical indicators and human oversight. This strikes a balance between accuracy, speed and trust in the decision-making process.

In conclusion, the transition to AI in credit scoring should not be seen as a complete replacement of traditional models, but as an opportunity to upgrade and adapt them to the challenges of modern financial reality.

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