Credit Risk Assessment in Banks Using Machine Learning: Insights from Industry Practice and a Case Study

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Abstract

Background: The study investigates differences between traditional and machine learning (ML) methods for credit risk assessment in banking, highlighting ML's role and performance as an emerging tool. **Objectives:** The paper explores credit risk assessment in banking practice and presents a case study of an ML tool in credit analysis to identify its effectiveness, challenges, and role in promoting financial inclusion compared with logistic regression. **Methods/Approach:** We used a mixed-methods approach. The focus was qualitative, using semi-structured interviews with representatives from Croatia's banking sector regulator and the five largest banks. We also applied quantitative analysis to the German Credit Dataset, using logistic regression as a traditional model and a decision tree as an ML model. **Results:** Expert interviews emphasized the importance of regulatory compliance and effective employee training in ML credit analysis. In quantitative analysis, logistic regression proved more accurate and easier to interpret, though it struggled to capture nonlinear patterns– potentially leading to the exclusion of some applicants–where the decision tree proved more successful. **Conclusions:** The study confirms that ML has potential in credit risk assessment because it can process extensive data quickly and effectively. However, it still has drawbacks to address, including interpretability, overfitting, accuracy, data quality, and regulatory compliance. The paper's findings may serve policymakers, as well as professionals and researchers in this field.

Keywords: credit risk assessment; machine learning; logistic regression; decision tree; financial inclusion

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Introduction

Credit risk assessment plays a vital role in risk management in the banking sector because of banks' business models and their influence on financial stability (Chang et al., 2025; Qian et al., 2025). Traditional methods like financial ratios, credit scoring, and logistic regression are still popular because they are simple, transparent, and accepted by regulators. However, advances in technology and the increasing amount of data have boosted interest in machine learning (ML) and deep learning (DL), in both academic and industry contexts. Machine learning algorithms have improved the accuracy of credit risk prediction, but still struggle with a lack of interpretability or transparency, which is a problem in the decision-making process (Chang et al., 2025). Additionally, regulatory approval has also been a challenge (Svetlova, 2022; Langenbucher, 2020).

This paper explores the effectiveness and challenges of machine learning in credit risk assessment compared with traditional tools. Because traditional financial approaches in credit risk assessment still limit access to financial services for various societal groups, this study also seeks to enhance recent research on machine learning solutions that promote financial inclusion—providing loans and other financial services to socially vulnerable, financially disadvantaged populations, and entrepreneurs—a topic of high relevance (Yasir et al., 2022; Kumar et al., 2021; Kshetri, 2021; Mhlanga, 2020). Therefore, we investigate traditional and machine learning solutions in credit risk assessment to determine how to improve loan applicant selection by better evaluating creditworthiness. Our research question focuses on identifying practices, challenges, and the potential for implementing machine learning in credit risk assessment. We also test whether machine learning delivers better results than traditional credit analysis.

The analysis uses both descriptive and comparative techniques alongside statistical modeling. We obtain qualitative insights from semi-structured interviews with regulators and banking practitioners about applying machine learning solutions in this area. Simultaneously, quantitative analysis employs logistic regression and decision tree models on secondary data. The empirical section encompasses:

- Qualitative analysis, based on interviews with representatives of the Croatian National Bank and experts from five banks in Croatia of different sizes, aimed at identifying practices, challenges, and the potential for implementing machine learning in credit risk assessment.
- Quantitative analysis, based on testing the effectiveness of logistic regression and decision tree models in credit analysis using the German Credit Dataset.

Compared with previous research, this paper adds value through a research design and methodological approach that combine qualitative and quantitative analyses. This paper's contribution is two-fold. First, the research findings evaluate how prepared the Croatian banking sector is to implement machine learning tools for credit risk assessment. The findings emphasize both the benefits and constraints of using advanced credit analysis models for banks and borrowers from the practitioners' and the regulator's perspective. Second, the paper contributes additional insights into the performance of machine learning and traditional credit analysis in identifying which offers a better solution.

After the introduction, the second part outlines the theoretical framework of credit analysis, reviewing relevant literature and regulatory standards for using machine learning in credit analysis. The third section presents the methodology, the fourth presents the empirical findings, and the final section discusses and concludes.

Literature review

The notion of credit risk and evolution of credit analysis

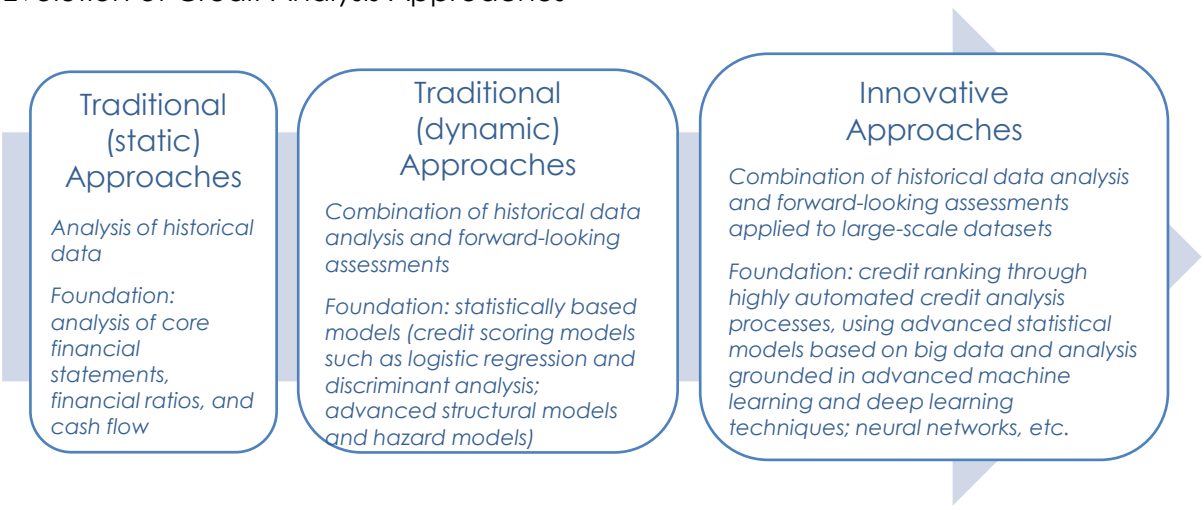
Credit risk involves the chance that a borrower cannot meet their financial obligations, making it central to banking operations. Given banks' key role in the financial system, credit risk is the most significant risk in financial sector management and a priority for banking supervision (Pokorna & Sponer, 2015). Effective management is especially important in the banking industry (Garcia et al., 2013) and vital for system stability (Chang et al., 2025). Therefore, assessing a borrower's creditworthiness, or credit analysis, is essential for sound credit risk management, the banking sector, and systemic stability (Qian et al., 2025).

Several methods predict debtors' default probability, including logit analysis and newer approaches based on neural networks or multicriteria methods (Garcia et al., 2013). Personal and corporate credit ratings differ, reflecting differences in assessment processes. Personal ratings classify (Le & Zhong, 2012) individuals as "good" or "bad" borrowers via automated procedures like scoring cards and rely on accessible data such as income, employment, debt, repayment history, accounts, and spending behavior. Corporate ratings, however, involve detailed, individualized analyses, including financial statements, ratios, business models, industry traits, and qualitative factors such as competitive position, market conditions, and strategy, because firms differ in heterogeneity, size, and international exposure. These assessments are more complex because firms' characteristics and external factors vary (Caplinska & Tvaronavičienė, 2020).

The static approach in credit analysis uses historical financial data and basic performance indicators. As methods advanced, tools like horizontal and vertical analysis and cash-flow analysis helped assess the applicant's financial health more thoroughly (Allen, 2013). The dynamic approach additionally focuses on cash-flow projections and qualitative evaluation, often using standardized statistical methods to estimate bankruptcy or default risk (Li & Zhong, 2012). These models combine financial forecasts with qualitative factors and rely less on static historical data.

Figure 1 presents the stages of evolution of credit analysis approaches.

Figure 1
Evolution of Credit Analysis Approaches



Source: Authors' illustration

Key factors to consider when choosing a bankruptcy prediction method are accuracy, complexity, implementation costs, data access, statistical appropriateness,

prediction timeframe, and industry-specific traits (Allen, 2013). Approaches for evaluating a company's creditworthiness and forecasting bankruptcy have evolved over time, driven by changes in financial markets, assessment tools, and regulatory standards (see Figure 1).

Traditional credit analysis

Traditional credit analysis primarily relies on statistical models, with credit scoring being the most common. This method ranks applicants using points derived from their historical data and financial indicators. The most commonly used methods for creating these scores include: (i) Discriminant analysis, which is simple and transparent but used less often due to assumptions of normality and equal variances. It finds a linear combination of variables that best distinguishes "good" from "bad" borrowers; (ii) Logistic regression, which analyzes a limited set of expert-selected variables to calculate a credit score, modeling the probability of being a "good" or "bad" borrower with a logistic (S-curve) function and does not require strict distributional assumptions. This method offers easy interpretation and regulatory approval (Skoglund & Chen, 2015; Allen, 2013; Li & Zhong, 2012).

Recent statistical scoring models also use historical data and financial ratios, combining specific indicators into a single index to assess corporate insolvency risk. This includes the Argenti (A-score, 1976) and Altman (Z-score, 1968) methods, with the Z-score being the first systematic use of discriminant analysis for bankruptcy prediction. Altman later developed the ZETA model (1977), which added more variables and extended the prediction timeframe to five years; similar models were later expanded.

Advanced structural models, particularly Merton's model from the 1970s, evaluate corporate credit risk by comparing a firm's asset market value to the value of its liabilities. This approach underpins modern corporate insolvency: if the assets' market value at maturity exceeds the liabilities' nominal amount, the borrower fulfills its obligations; if not, default occurs, and creditors take control of the assets. The model also presumes that shareholders have an implicit option on the firm's assets (Skoglund & Chen, 2015; Allen, 2013).

Hazard models, in contrast, assess credit risk through the hazard rate, which indicates the likelihood of default within a very short period. They examine time-to-default based on observed traits and historical data, effectively modeling its distribution (Roncalli, 2020; Skoglund & Chen, 2015). Consequently, hazard models serve as an alternative to structural models by directly estimating default intensity as a function of time and relevant factors, without depending on assumptions about asset value dynamics.

In summary, traditional credit risk assessment methods combine financial and non-financial data. For corporate clients, this typically involves analyzing financial statements and key indicators like liquidity, leverage, and profitability. These elements are often implemented through credit scoring models, enabling standardized, transparent, and regulatorily compliant evaluations of creditworthiness. While these approaches are straightforward and easy to interpret, their primary drawback is their limited capacity to detect nonlinear relationships and complex data patterns.

Machine learning credit analysis

Recent technological advances and the rapid expansion of available data (Amarnadh & Moparthi, 2023), combined with the limitations of traditional models in handling large, unstructured, and complex datasets, recognizing nonlinear relationships, and adapting to changing market conditions, have challenged credit risk analysis to a large extent (Derera, 2016). These factors have enabled the

emergence of credit analysis tools, specifically deep learning and machine learning techniques, supporting highly automated, big data-driven credit assessment processes to improve performance and address issues in the banking sector by focusing on business processes and customer interactions (Amarnadh & Moparthi, 2023). Such methods use large datasets and advanced algorithms to deliver more accurate, faster, and more adaptable credit risk assessments.

Advanced credit risk assessment techniques leverage complex behavioral patterns and variable interactions to boost prediction accuracy and process efficiency (Chang et al., 2025). However, they also pose interpretability and regulatory approval challenges (Svetlova, 2022; Langenbucher, 2020). While technologically innovative solutions can enhance forecasting and customer segmentation, in practice, they operate within a highly regulated, standardized banking framework.

Recent empirical studies increasingly indicate that advanced machine learning techniques often surpass traditional statistical models in credit risk evaluation, particularly when dealing with complex, nonlinear data. Pratiwi et al. (2023) emphasized the main benefit of these advanced techniques: their forward-looking perspective compared with conventional, non-forward-looking methods. Wang et al. (2020), when comparing several classifiers such as logistic regression, decision trees, and random forests, found that random forests provided the best accuracy and precision, while logistic regression was valued for its interpretability and stability.

Shi et al. (2022) confirmed that ensemble methods and deep learning usually outperformed traditional models in predictive accuracy, highlighting banking challenges such as data imbalance, limited interpretability, and regulatory constraints. This aligns with Le et al. (2025), which found that advanced ensemble learning techniques in machine learning and deep learning improve default prediction (with higher precision). Analysis of alternative data sources, such as social media and non-traditional financial indicators, showed the additional potential of advanced technology to help assess client creditworthiness (Chen & Chen, 2022).

Despite obstacles related to transparency, regulatory compliance, and consumer trust (Sinha & Lee, 2024), machine learning plays a beneficial role in financial inclusion, risk management, and decision-making. Kumar et al. (2021) note that machine learning credit analysis improves financial inclusion for socially vulnerable and underserved populations by giving them access to credit and microcredit beyond basic accounts. Mhlanga (2020) stressed that financial institutions and other stakeholders should adopt and expand advanced technological tools across all sectors, as they can bring financially inactive individuals into the formal financial system with minimal difficulty and maximum advantage. Ultimately, in line with previous technological advances in finance, machine learning tools used in credit risk assessment also boost profitability and efficiency (Kaya, 2019).

Machine learning solutions, while useful, also have several limitations, underscoring the need to assess the effectiveness of more advanced credit analysis models, such as machine learning, relative to traditional approaches.

Regulatory standards for using machine learning in credit analysis

The Basel standards and related prudential regulations specify how banks should manage risk and determine regulatory capital based on assessed risk. The Basel frameworks have driven major advancements by allowing banks to use Internal Ratings-Based (IRB) systems.

Banks can develop their own models to estimate three crucial credit risk metrics: Probability of Default (PD), which indicates the chance a borrower will default; Loss Given Default (LGD), representing the portion of an asset lost if default occurs; and

Exposure at Default (EAD), the total amount exposed at the time of default (Regulation (EU) 2024/1623 amending Regulation (EU) No 575/2013 as regards requirements for credit risk, credit valuation adjustment risk, operational risk, market risk and the output floor, CRR III). These metrics are vital for calculating Expected Loss (EL). However, deploying advanced credit risk models poses significant challenges, as banks must validate that their models are conservative and transparent. Basel III mandates validation, detailed documentation, and stability during stress scenarios. More advanced technologically innovative models, such as neural networks, however, face interpretability and transparency issues that can hinder regulatory approval under the IRB approach.

Overall, meeting Basel requirements remains a key obstacle to adopting technologically advanced methods across banking segments, though larger banks tend to lead in implementing sophisticated credit risk assessment methods.

Machine learning is still rarely used in the regulatory domain (IRB, IFRS 9, stress tests), however, recent discussions initiated by the European Banking Authority suggest that this may change in the near future (Hurlin & Perignon, 2023). This stems from technical complexity, but machine learning models offer the prospect of better credit risk measurement and enhanced financial inclusion (Hurlin & Perignon, 2023).

Because transparency, explainability, and ethical considerations are crucial (Sinha & Lee, 2024), banks and regulators demand clear model explanations, data protection, bias reduction, and a focus on social responsibility alongside financial inclusion. Advanced tools can greatly improve credit assessment but cannot fully replace traditional methods, especially in highly regulated areas like credit risk management (Sinha & Lee, 2024).

In conclusion, these models succeed when data quality is high, validation is thorough, human oversight is maintained, and explainable solutions meet regulatory standards and build client trust.

Methodology

Qualitative research

Semi-structured interviews were conducted to (i) assess current credit risk evaluation methods, including experience with machine learning solutions, and to (ii) gain additional insights into interviewees' awareness of their advantages and limitations, perceived accuracy, effectiveness, and analytical risks, and to (iii) gauge the Croatian banking sector's preparedness for technologically advanced credit analysis. Semi-structured interviews were selected as an appropriate qualitative research method because they enable the systematic collection of expert insights while allowing sufficient flexibility to capture context-specific knowledge in complex, highly regulated environments. Similar approaches have been widely applied in financial and organizational research to explore emerging technologies and decision-making processes (Jerman et al., 2020; Pejić Bach et al., 2019).

Interviewees were chosen based on their expertise in credit risk management and their professional roles related to technologically innovative approaches in credit risk assessment (Table 1). The sample comprised a regulator interviewee from the Croatian National Bank (R) and five interviewees from Croatian banks (KI1-5) of varying sizes. The selection of interviewees from the banking sector aimed to ensure representation across all bank size categories: two large banks (with over 5% of total sector assets—KI1 at 17.9% and KI2 at 8.4%), one medium-sized bank (1%–5%—KI3 at 1%), and two

small banks (under 1%—KI4 at 0.4% and KI5 at 0.3%). We applied content analysis to the collected data.

Table 1
The Structure of Interviewees

Bank	Job Position	Gender	Relation to Implementation of Technologically Innovative Models in Credit Risk Assessment
KI1	Credit Risk Manager	Female	Provides expert insights into credit risk assessment for SME clients.
KI2	Customer Support Manager	Male	Offers a customer-facing perspective on automated credit decision processes.
KI3	Senior Trade Finance Specialist	Female	Provides a trade finance and transaction banking perspective on credit risk.
KI4	Director	Female	Provides a top-management perspective on the adoption of ML solutions in credit risk management.
KI5	Credit Risk Analyst Retail Credit Risk Analyst	Male 2 Female	Provides an operational perspective on credit risk assessment (three interviews: one with a credit risk analyst and two with retail credit risk analysts).
R	Senior Advisor for Credit Risk Models and Regulation	Female	Offers a regulatory perspective on ML solutions in credit risk assessment.

Source: Authors' work

Quantitative research

The quantitative analysis is presented as an illustrative case study to visually demonstrate differences between traditional and machine learning solutions in credit risk assessment, rather than as a comprehensive performance evaluation. Accordingly, we applied two widely used, conceptually distinct models (Table 2): logistic regression as a traditional reference approach and a decision tree as a simple nonlinear machine learning method. We conducted the analysis using the Python scikit-learn library, following Pedregosa et al. (2011).

Table 2
Characteristics of the Models tested

Model	Description
Logistic regression	A traditional statistical model used as the reference approach; applied with an increased number of iterations (max_iter = 2000) to ensure convergence and high interpretability of the results.
Decision tree	An ML model capable of capturing nonlinear relationships; constrained to a maximum depth of 3 (max_depth = 3) to reduce overfitting and enhance model interpretability.

Source: Authors' work

Testing was performed in Google Colab using the publicly accessible German Credit Dataset, a common benchmark in academic credit scoring studies (UCI Machine Learning Repository).

The dataset includes 1,000 entries—each representing a client applying for bank credit—and 21 categorical features: 20 predictor variables and one target variable indicating creditworthiness (Good/Bad); see Table 3. We transformed categorical variables using one-hot encoding and kept numerical variables in their original form.

For testing, we encoded categorical variables and split the dataset into training and test sets. The models were assessed using standard performance metrics to evaluate their accuracy, interpretability, and robustness:

- Accuracy – the percentage of correctly classified clients.
- AUC (Area Under the Receiver Operating Characteristic Curve) – the capability of the model to distinguish between „good" and „bad" borrowers, following the framework and methodology proposed by Fawcett (2006).
- Precision – the proportion of clients labeled as high-risk who are truly in the "bad" category.
- Recall – the percentage of actual high-risk clients that the model correctly detected.
- F1-score – a combined metric of precision and recall, especially useful when there is class imbalance.

To ensure reproducibility, we used a random state parameter, and we selected hyperparameters (e.g., max_depth) to reduce overfitting. In addition, we used cross-validation to assess the robustness of the results. We evaluated the decision tree model's interpretability by analyzing its structure, which identified the key features most influential in the credit decision-making process (transaction account status, loan maturity, and credit history).

This design enabled a clear comparison between the traditional and machine learning approaches and confirmed the key advantages and limitations of each model in banking practice.

Table 3
Predictor Variables and Encoding Approach Used

Variable	Question	Answers	Type
Checking_ account_status	Status of the applicant's transaction account	No checking account; negative balance; balance below threshold; balance above threshold	Categorical (one-hot encoded)
Credit_history	Applicant's past credit repayment behavior	No credits taken; all credits paid duly; existing credits paid duly; delays in the past; critical account	Categorical (one-hot encoded)
Purpose	Purpose of the requested loan	Car (new); car (used); furniture/equipment; radio/TV; domestic appliances; repairs; education; business; vacation; retraining; other	Categorical (one-hot encoded)
Savings_account/ bonds	Level of savings or bonds held by the applicant	No savings; low savings; moderate savings; high savings	Categorical (one-hot encoded)
Employment	Employment status and duration	Unemployed; employed <1 year; employed 1–4 years; employed ≥4 years	Categorical (one-hot encoded)
Housing	Applicant's housing status	Rent; own; free	Categorical (one-hot encoded)
Other_instalment_ plans	Existence of other installment obligations	None; bank; stores	Categorical (one-hot encoded)
Personal_status/ sex	Marital status and gender	Male single; male married/widowed; male divorced/separated; female	Categorical (one-hot encoded)
Foreign_worker	Foreign worker status	Yes; no	Categorical (one-hot encoded)
Duration	Loan duration (in months)	Numeric value (months)	Numerical

Credit_amount	Amount of the requested loan	Numeric value (currency units)	Numerical
Instalment_rate	Installment rate as a percentage of income	Numeric value (1–4 scale)	Numerical
Age	Age of the applicant	Numeric value (years)	Numerical
Number_of_ existing_credits	Number of existing credits held by the applicant	Numeric value	Numerical
Other_debtors	Existence of other debtors or guarantors	None; co-applicant; guarantor	Categorical (one-hot encoded)
Property	Type of property owned by the applicant	Real estate; life insurance; car or other; none	Categorical (one-hot encoded)
Job	Type of employment / job category	Unemployed/non-resident; unskilled; skilled; management/self-employed	Categorical (one-hot encoded)
Telephone	Availability of a telephone	Yes; no	Categorical (one-hot encoded)
Residence_since	Length of residence at current address	Numeric value (years)	Numerical
Number_of_ dependents	Number of dependents	Numeric value	Numerical

Source: Authors' work using German Credit Dataset

Results

Practice of using machine learning in credit risk assessment in Croatian banks

Table 4 shows aggregated findings from the interviews, followed by a more detailed presentation of the content analysis results, separately for the regulatory institution interviewee and the bank interviewees.

Table 4

Thematic Framework of the Semi-structured Interviews, Questions and Aggregated Findings

Topic	Questions	Key findings
Current credit risk assessment practices	How is credit risk currently assessed in your institution?	Traditional models (logistic regression, scorecards, expert judgment) remain dominant due to transparency and regulatory acceptance.
Application of ML solutions in credit risk assessment	Are ML solutions currently used or tested in credit risk assessment?	ML solutions are mainly tested in larger banks, primarily in retail banking; smaller banks do not currently apply ML solutions.
Importance of interpretability and regulatory compliance of credit risk assessment model	How important are model explainability and its regulatory compliance?	Explainability is essential; regulatory requirements (Basel III, GDPR, AI Act) and ethical considerations (responsible use and adequate oversight) limit the use of black-box models.
Data and organizational constraints of ML	What are the main barriers (advantages and limitations) to	Limited data quality, lack of resources, and organizational readiness constrain ML solutions implementation.

solutions in credit risk assessment	implementation of ML solutions?	
Human oversight in credit risk assessment and future outlook	Can ML solutions replace human credit analysts in future?	ML solutions are viewed as a supporting tool with gradual adoption expected; human oversight remains indispensable.

Source: Authors' work

The regulator's representative indicated a cautious approach to machine learning solutions in bank credit risk assessment. Traditional models like logistic regression, scorecards, and expert systems remain dominant due to their transparency, interpretability, stability, and regulatory acceptance. The regulator emphasized that 'black-box' models can pose issues because of their complexity, limited explainability, and potential for discrimination. They also pointed to insufficient digitalization and data quality, which hinder machine learning credit risk modeling that requires large, reliable datasets. These issues underscored supervisory requirements for explainability, governance, validation, and human oversight.

The significance of model explainability is also highlighted by the regulator's representative, especially regarding personal data protection (Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the processing of personal data and the free movement of such data, repealing Directive 95/46/EC - the General Data Protection Regulation; GDPR). This is particularly relevant in light of Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024, which establishes harmonized rules for AI (AI Act) and bans fully automated decision-making with legal effects without human oversight. Variables that could lead to discrimination—such as age or gender—must be excluded from models, adding challenges for systems that depend on unstructured or alternative data. Although regulators have not issued specific machine learning guidelines for credit risk assessment, all models must adhere to principles of proportionality, conservativeness, and understandability, and must comply with Basel standards. Despite regulators' cautious stance on implementing machine learning models in bank credit risk assessments, support exists for creating regulatory sandbox environments—controlled testing spaces where machine learning solutions can be evaluated safely, reducing risks to system stability (Merriam-Webster, n.d.).

Interviews with representatives from selected banks highlight noticeable differences in current credit risk management practices and their willingness to adopt machine learning models for credit assessment. Interviewees from larger banks—especially those belonging to international banking groups—show greater readiness to implement advanced machine learning credit risk assessment models, mainly because they follow their parent institutions' strategies and guidelines. These banks already provide internal training in that direction and are either planning to test or have already adopted advanced analytics and automation tools, such as chatbots or internal scoring systems that include machine learning features. Conversely, smaller banks, which focus on local markets and niche areas, stress that they currently lack the capacity and necessity to implement technologically more advanced tools. They mainly rely on traditional methods, credit analysts' subjective judgment, and HROK, the national central repository of client credit data.

The larger banks in the sample (KI1 and KI2) have greater financial and organizational resources, allowing them to invest in sophisticated analytical tools and deploy machine learning solutions in credit risk analysis. Representatives from these large banks mentioned running pilot projects with machine learning, mainly in the retail segment where processes are more standardized. They also provide internal

training and build employees' digital skills, aligning with their international parent companies' strategies. Respondents believe advanced machine learning tools can enable faster, more efficient application processing, improved client segmentation, fraud detection, and more predictive credit risk models. KI1 emphasized the limited applicability of fully automated and machine learning models for larger exposures and highlighted the continued importance of human oversight, qualitative information, and regulatory constraints, while recognizing the potential of machine-learning-based models to improve efficiency and speed in lower-risk, standardized credit processes (a strategic and governance perspective). KI2 interviewee focused on explainability, client communication, and the handling of inquiries and complaints arising from scoring-based credit outcomes (customer-facing perspective).

In contrast, medium-sized and smaller banks (KI3–KI5) are much more cautious about adopting technologically advanced credit analysis models. These banks mainly rely on traditional credit risk assessment methods such as scorecards and subjective judgments by credit analysts. They often cite limited technical and financial resources, difficulty hiring specialized staff, and uncertainty about regulatory compliance—particularly with GDPR and Basel standards. Concerns about bias and transparency in machine learning solutions also slow down adoption. Consequently, smaller banks' digital transformation progresses more slowly, and they see machine learning solutions as a long-term opportunity rather than an immediate solution. KI3 interviewee emphasized the role of digital platforms and automated control systems in managing guarantee-related risk, and highlighted the extensive use of rule-based systems, integrated data checks, and automated validations to assess client eligibility, monitor exposures, and reduce operational risk, while stressing that final credit-related decisions—particularly for larger exposures—remain subject to human oversight due to regulatory requirements, qualitative considerations, and the need for assessment beyond predefined parameters (a process and operational risk perspective). The KI4 interviewee focused on strategic priorities, organizational readiness, and governance considerations, and emphasized a cautious, phased approach to digital transformation that balances efficiency gains from automation with regulatory compliance and the continued need for human oversight in credit decision-making (top-management perspective). KI5 interviewees highlighted the widespread use of internal scoring and rating models combined with extensive manual analysis and human judgment, particularly in retail and SME lending, and emphasized the potential of machine learning solutions to accelerate data processing, reduce documentation burden, and support consistency in decision-making, while stressing that final credit decisions should remain subject to human oversight due to regulatory requirements, qualitative factors, and client-specific circumstances (an operational perspective).

All bank respondents highlighted that current credit risk assessment challenges mainly stem from a lack of high-quality, up-to-date data, especially in the corporate sector, where fewer clients exist and assessments tend to be more personalized. Decisions depend heavily on detailed evaluations of individual companies and expert judgment, which hinder standardization and complicate the adoption of machine learning solutions in credit risk analysis. In retail banking, with larger client bases and more uniform behavioral patterns, standardized scoring systems are already prevalent, showing greater promise for automation and process consistency. However, even here, banks emphasize the need for human oversight and transparent credit evaluation models. As a result, the human element remains essential in the credit analysis process.

The qualitative analysis indicates that the Croatian banking sector mainly depends on traditional credit risk assessment models. While technologically advanced tools are

considered a long-term opportunity, their adoption depends on satisfying regulatory and operational standards. Larger banks are at the forefront of testing advanced analytical solutions, whereas smaller banks face resource limitations and challenging implementation demands. The regulator emphasizes that transparency, explainability, and human oversight are crucial for the safe use of machine learning solutions in future credit risk evaluations.

Illustrative Case Study

Table 5 compares the results of a logistic regression model and a decision tree model.

Logistic regression achieved higher overall accuracy (81% vs. 71%) and a superior AUC (0.818 vs. 0.666), indicating better generalization to the test set and more precise discrimination between "good" and "bad" clients. It was particularly effective at identifying "good" clients, with 0.83 precision and 0.91 recall. However, both models performed worse on the "bad" class. Although logistic regression yielded higher precision (0.72 vs. 0.51 for the decision tree), recall remained low (0.56 for both models), reflecting the dataset's class imbalance, as confirmed by the support values.

Table 5

Results of the Logistic Regression Model (left) and the Decision Tree Model (right)

Logistic Regression					**Decision Tree**				
accuracy	0.805				**accuracy**	0.710			
AUC	0.818				**AUC**	0.666			
clients:	precision	recall	f1-score	support	**clients:**	precision	recall	f1-score	support
0-bad	0.72	0.56	0.63	59	**0-bad**	0.51	0.56	0.53	59
1-good	0.83	0.91	0.87	141	**1-good**	0.81	0.77	0.79	141
macro average	0.77	0.73	0.75	200	**macro average**	0.66	0.67	0.66	200
weighted average	0.80	0.81	0.80	200	**weighted average**	0.72	0.71	0.71	200

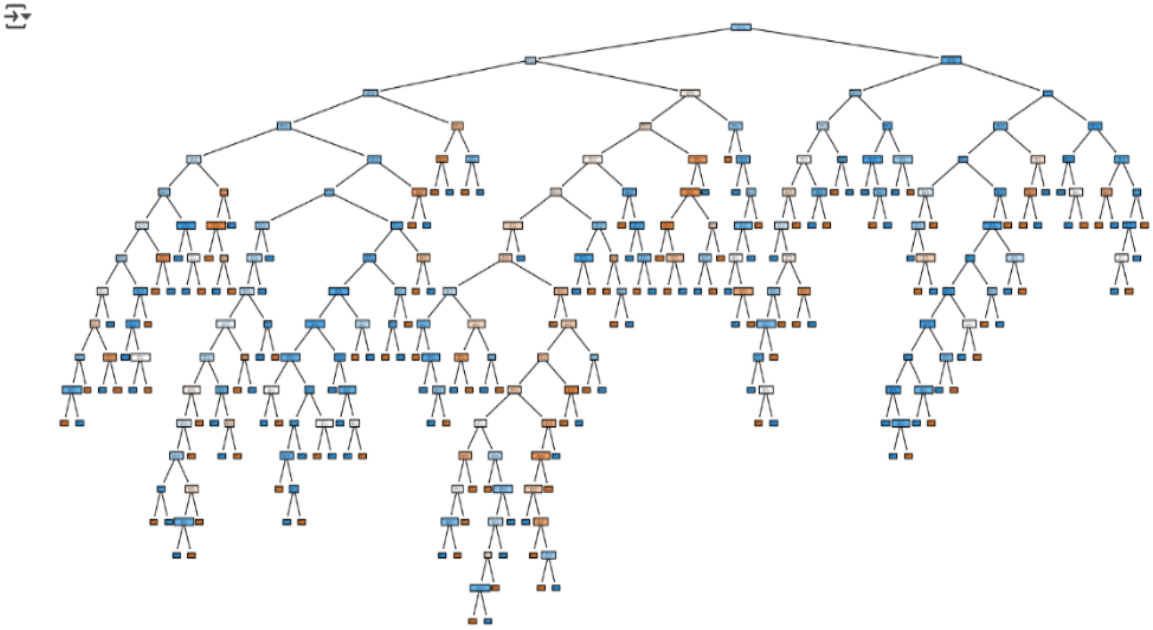
Source: Authors' calculation in Google Colab by using German Credit Dataset

The decision tree performed worse across most metrics, partly due to the depth constraint and partly because of its inherent susceptibility to overfitting. Its main advantage, however, is its ability to capture non-linear patterns. The tree structure clearly reveals the variables most influential in the decision process (e.g., transaction account status, loan maturity, and credit history). This makes it valuable when model transparency is prioritized over predictive performance. Its tendency toward overfitting aligns with both the literature (e.g., Halabaku & Bytyçi, 2024) and practical banking experience.

An unconstrained decision tree model was first estimated to demonstrate the typical problem of overfitting in machine learning-based credit risk models (Figure 2).

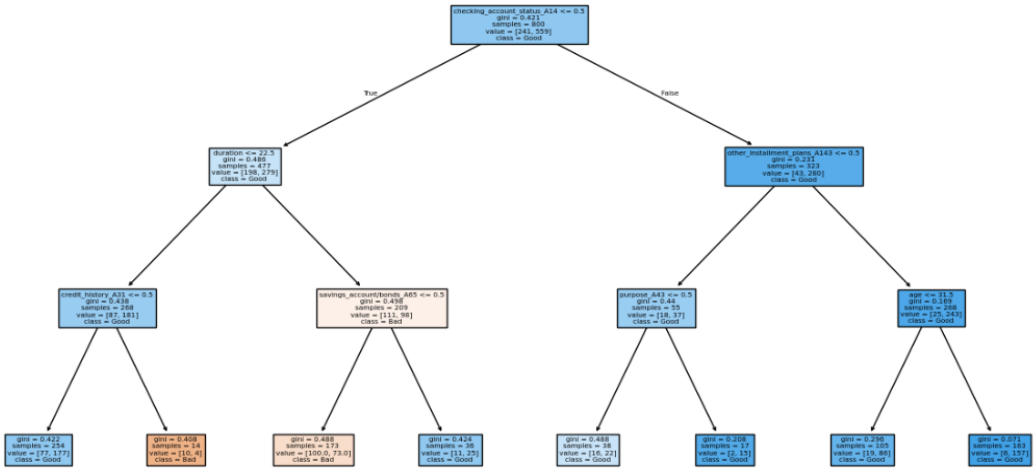
Although models like the one shown in Figure 2 can achieve high in-sample accuracy, their complexity, low interpretability, and instability make them unsuitable for practical banking applications. To address these limitations, we constrained the decision tree model by limiting its maximum depth to three levels, resulting in a pruned, more interpretable model (Figure 3).

Figure 2
Visualization of The Decision Tree without Depth Constraints (Overfitted Model)



Source: Authors' work using German Credit Dataset in Google Colab

Figure 3
Visualization of The Decision Tree with a Depth Limit to 3 (Pruned Model)



Source: Authors' work using the German Credit Dataset in Google Colab

Both Figure 2 and Figure 3 visualizations emphasize the difference between overfit and constrained models and highlight overfitting concerns in complex trees, findings confirmed by the quantitative evaluation results. Figure 2 illustrates an unconstrained decision tree that represents a typical overfitted model, characterized by high complexity and limited interpretability. In contrast, Figure 3 presents a pruned decision tree with a maximum depth of three, resulting in a simpler and more transparent model.

The following attributes were used to develop the pruned decision tree (Figure 4): Checking Account Status, Credit History, Duration, Savings Account/Bonds, Other Installment Plans, Purpose, and Age.

Figure 4
The Pruned Decision Tree Model Developed with Algorithm-Selected Attributes

```
checking_account_status_A14 <= 0.5
| duration <= 22.5
| | credit_history_A31 <= 0.5 : Good
| | credit_history_A31 > 0.5 : Bad
| duration > 22.5
| | savings_account/bonds_A65 <= 0.5 : Bad
| | savings_account/bonds_A65 > 0.5 : Good
checking_account_status_A14 > 0.5
| other_installment_plans_A143 <= 0.5
| | purpose_A43 <= 0.5 : Good
| | purpose_A43 > 0.5 : Good
| other_installment_plans_A143 > 0.5
| | age <= 31.5 : Good
| | age > 31.5 : Good
```

Source: Authors' work using German Credit Dataset

Limiting tree depth reduces overfitting and improves practical applicability, particularly in regulated banking environments where model explainability matters. To further support interpretation, Table 6 summarizes the main decision rules derived from Figure 3, translating the tree structure into clear IF–THEN conditions.

Table 6
Decision Rules Extracted from the Pruned Decision Tree Model

Rule	Decision path (IF conditions)	Predicted credit risk
Rule 1	IF the applicant has no favorable checking account status AND short loan duration AND poor credit history	Bad
Rule 2	IF the applicant has no favorable checking account status AND short loan duration AND good credit history	Good
Rule 3	IF the applicant has no favorable checking account status AND longer loan duration AND low savings	Bad
Rule 4	IF the applicant has no favorable checking account status AND longer loan duration AND adequate savings	Good
Rule 5	IF the applicant has a favorable checking account status AND no other installment plans AND non-consumption loan purpose	Good
Rule 6	IF the applicant has a favorable checking account status AND no other installment plans AND consumption loan purpose	Good
Rule 7	IF the applicant has a favorable checking account status AND other installment plans AND age above 31.5 years	Good
Rule 8	IF the applicant has a favorable checking account status AND other installment plans AND age below or equal to 31.5 years	Good

Source: Authors' work using German Credit Dataset

Overall, logistic regression showed greater reliability for baseline credit risk assessment, while decision trees offer advantages in capturing nonlinear patterns, in addition to their general advantage in managing extensive data. These results are consistent with previous research. Kumar et al. (2021) identify logistic regression as a reference model due to its stability and interpretability, though it has limitations in modeling nonlinear patterns, which can lead to the financial exclusion of some applicants. On the other hand, decision trees are more adaptable but tend to be less precise and more susceptible to overfitting — a pattern observed in this study. Decision trees can perform significantly better within ensemble learning methods (e.g., Random Forest, Gradient Boosting (Derera, 2016)), where their predictive accuracy can rival or surpass logistic regression. Overall, the findings suggest that a single model is not sufficient in real-world scenarios. Instead, choose the model based on the goal—be it accuracy, regulatory compliance, or transparency. Also, one should consider that financial inclusion matters, especially if sustainable financial practices are important to financial institutions.

Discussion and Conclusion

This study provides a theoretical and empirical review of traditional and advanced tools for credit risk assessment in banking, offering insights into how different methods contribute to credit risk management. Specifically, it offers important insights into the current state, perceptions, and expectations regarding machine learning tools in credit risk evaluation within the Croatian banking industry. Results indicated that the market primarily favors traditional approaches and remains cautious about adopting sophisticated automated solutions. This aligns with Croatia's broader economic and social environment, factors recognized as relevant (e.g., Chien et al., 2020; Gillespie et al., 2023), where both institutions and consumers are relatively cautious about using fully automated systems. Qualitative insights emphasized caution in adopting ML credit analysis, despite benefits such as improved efficiency, more thorough analysis, and straightforward results confirmed in some studies (e.g., Pratiwi et al., 2023; Le et al., 2025). Ethical and regulatory factors are particularly crucial in this context (Sinha & Lee, 2024).

Technologically advanced models can boost predictive accuracy, and by incorporating a wider range of parameters and data sources potentially enhance financial inclusion for certain social groups that are often unjustly denied access to credit (e.g. Hurlin& Pérignon, 2023; Kshetri, 2021; Kumar et al., 2021). However, these models pose challenges such as overfitting (e.g., Halabaku & Bytyçi, 2024), interpretability (e.g., Chang et al., 2025), bias, data privacy, and regulatory issues (e.g., Sinha & Lee, 2024). Regulations such as GDPR and the EU AI Act demand transparency and ban fully automated decisions with legal effects. Meanwhile, Basel standards require cautious, stable, and well-validated models, limiting the use of complex 'black-box' models in banking. To promote responsible use of advanced tools in credit analysis, regulators and banks focus on explainable models, human oversight, high-quality data, and regulatory sandbox environments for safe testing. This technologically advanced approach offers a promising opportunity to improve credit risk assessment, but its sustainable adoption relies on gradual implementation, clear regulations, and responsible risk management.

The quantitative analysis reaffirmed that logistic regression remains the preferred method in practice because of its simplicity and transparency; Kumar et al. (2021) identified it as a reference model, making it acceptable to regulators. However, it struggles to capture nonlinear patterns and has limitations in managing large datasets (Derera, 2016).

Although decision trees were less accurate and prone to overfitting, their visual clarity and interpretability remain valuable for communicating with clients and regulators. However, deploying machine learning for credit analysis is complicated by technical, ethical, and regulatory challenges (Sinha & Lee, 2024).

Given the above, one should consider that a single model is not sufficient in real-world scenarios. The model should be chosen based on the goal—be it accuracy, regulatory compliance, or transparency —in accordance with Sinha & Lee (2024).

While the study offers valuable insights into current practices and challenges in machine learning solutions in credit risk assessment, several limitations should be acknowledged. These include a qualitative analysis confined to a national scope, a cross-sectional quantitative design, and a single-country dataset that is not broadly generalizable, highlighting areas for future research. The qualitative analysis involved only a limited number of institutions in one country, while expanding the interview sample would provide a more comprehensive perspective. The cross-sectional approach used in the quantitative analysis captures data at a single point in time, preventing the establishment of cause-and-effect relationships and limiting the ability to observe changes over time. Finally, a small, publicly available dataset does not fully reflect the complexity of a specific banking sector (as in Croatia). Therefore, future studies should use a longitudinal research design and larger, more representative datasets and interview samples. Additionally, studies could explore the effects of employee training, regulatory sandbox environments, and the evolving regulatory landscape, as well as test more advanced models.

Overall, the Croatian banking sector seems to be in a stage of cautious exploration and readiness to implement advanced credit risk assessment tools. Machine learning solutions, valued for their predictive accuracy, speed, and thorough analysis, are highly useful and adaptable tools for credit risk evaluation; however, they should primarily complement, not replace, traditional methods. Although these models can speed up and improve credit analysis by quickly handling extensive data, the credit analyst remains crucial for oversight and final decisions. Therefore, a cautious approach continues to dominate, prioritizing stability, transparency, and regulatory compliance while acknowledging both the advantages and potential risks of using machine learning solutions in credit risk assessment.

In conclusion, our results indicate that machine learning solutions have significant potential to enhance credit risk assessment, but widespread adoption will require careful implementation, clear regulations, responsible risk management, and sustainable finance practices.

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