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Ability to Borrow Modeling Techniques for Small and Medium-Sized Enterprises

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This study comprehensively evaluates the ability to borrow machine learning modeling techniques for SMEs, utilizing a sample of the Baltic States with many variables. The study aims to assess the applicability of access to credit modeling techniques for SMEs. This is the first study in which a large–scale assessment has been carried out in the Baltic States sample, covering five years of credit applications from SMEs to a depository institution. The results showed that Gradient Boosting produces the most accurate results. Gradient Boosting demonstrated better results than the benchmark Logistic Regression as well as other advanced machine learning models, including Random Forests and Multilayer Perceptron models. The method showed the highest accuracy of the overall receiver operating characteristic (ROC) curve and the associated area under the curve (AUC) (ROC–AUC) and Average Precision values, as well as other discriminatory threshold values, compared to alternative methods.

Keywords: *SMEs; Ability to Borrow; Machine Learning Methods; Gradient Boosting; The Baltic States.*

Introduction

The role of small and medium-sized enterprises (SMEs) in both global and national economies is undeniable. These companies face many challenges and constraints, and according to Muller *et al*. (2022), the most important obstacle is constrained access to external financing. More than 30 percent of SMEs indicate a lack of ability to borrow. The lack of sufficient financial resources not only limits the growth of these companies but also reduces their resilience and threatens their survival. (ECB, 2022). Constrained access to external funding results in lower sales, decreased financial performance of companies, and supply chain disruptions. These factors negatively impact growth opportunities, forcing SMEs to cease activity (Khan, 2022). Whenever there is not enough official access to credit, informal credit funding is observed. In the long run, both informal credit arrangements and the shadow economy hamper SMEs' development (Sekyi *et. al.,* 2020). The ability to borrow is a significant limitation for businesses and is a particularly considerable obstacle for SMEs. Being small, these companies are sensitive to facing constraints that hamper their growth opportunities, resulting in lower economic development. Bongomin *et al.* (2024) emphasize that access to credit ability promotes the survival of small and medium companies in developing countries after the COVID-19 pandemic. According to Mistrean *et al.* (2022), SMEs need to be financed smartly. Especially the innovation and creativity of such companies should be supported. In this way, less developed countries can limit the technological gap and ensure sustainable enlargement of the whole economy, as the share of SME companies is equal to more than 99 percent of enterprises in Japan, the USA, and the EU. Each country, even in market–oriented economies, provides a specific way of credit access. For example, in Italy and Austria, banks are more eager to finance SME companies when pro-activeness, autonomy, and competitive aggressiveness are observed (Beltrame *et al.,* 2023). Consequently, the development of the ability to borrow modeling techniques for SMEs is very relevant. Accurate and transparent access to credit models and techniques could assist lenders in evaluating the creditworthiness of SMEs more accurately. These models can be built on various data sources beyond financial statements, which may not fully reflect the ability of SME to repay loans. However, SMEs are characterized by higher risk, which determines access to credit, which is why financial institutions need to have well-developed credit scoring systems to more accurately reflect true risk and improve lending decisions.

According to Wen *et.al.* (2022), credit risk management is a critical function for financial institutions. These institutions must minimize losses while maximizing profits, making risk assessment for each client vital. Credit risk assessment involves calculating the likelihood of financial loss. With the vast amount of available data, this task can be quite complex. It is crucial to identify which data is genuinely important and how it impacts the assessment. Therefore, the integration of technology in financial institutions and the use of advanced data processing methods are essential for accurately predicting risk (Amarnadh & Moparthi, 2023). In scientific literature (Molina & Preve, 2012; Pal *et al.,* 2016; Kruppa *et al.,* 2013), various abilities to borrow modeling methods were analyzed, emphasizing the perceived creditworthiness of the credit applicant.

Machine learning algorithms are fundamentally changing the processes of financial institutions related to credit risk assessment. Traditional methods like Logistic Regression have become challenging to apply to large datasets with interdependent variables (Bahnsen *et al.,* 2016). Meanwhile, machine learning algorithms are able to process large and diverse data samples and model complex, nonlinear dependencies. With the help of these methods, it is now possible to improve the accuracy of credit risk assessment.

The credit risk scoring model is usually a vital technique for assessing credit risk related to customer features that affect evasions (Ismawati *et al.*, 2023). Recently, the demand for machine learning methods has increased because they reduce bias and improve the accuracy of credit risk assessment models. In the studies (Malakauskas & Lakstutiene, 2021, Gu *et al.,* 2025, and Medianovskyi *et al.,* 2023) Multi–layer Perceptron (MLP), Gradient Boosting (GB), Support vector machines (SVM), and Random Forest methods in the valuation of SMEs' ability to borrow and showed prospective results. However, according to Preece et al. (2018), each method has its own strengths and weaknesses. The choice of the most appropriate technique depends on the specific problem being solved. It is important to note that interpretability of deep learning models is difficult, as it is not easy to understand how these models carry out their internal decisions, therefore, according to Arrieta et al. (2020), Arya et al. (2019), this complexity requires the use of explainability methods. Despite some limitations of the models, machine learning algorithms can increase models of SMEs' ability to borrow accuracy and applicability as they can identify nonlinear dependencies and interactions between variables.

While much research has been done on individual factors and their groups, the significance of each group, as well as individual factors and interactions, is still opaque. Evaluating the creditworthiness of SMEs is a complex issue that necessitates a systematic approach. This involves clearly defining SME creditworthiness, identifying the key factors to be used in modeling, and choosing suitable modeling methods to create an accurate and interpretable model. The scientific literature lacks a thorough methodology for assessing SME creditworthiness. Given the limited research on this topic, particularly in the context of credit risk assessment using machine learning techniques, this study offers the first comprehensive evaluation of SME creditworthiness through credit modeling methods, based on a sample from the Baltic States.

The aim of the research is to assess the applicability of access to credit modeling techniques for SMEs.

This research aims to fill the gap in existing knowledge on machine learning techniques in credit evaluation and expand the research that utilizes financing applications of SMEs to assess SMEs' ability to borrow. The significance of this topic and the research problem lies in the necessity to develop modeling algorithms that can thoroughly evaluate the accessibility of credit and the determinants that are crucial for SMEs to access financing. The scientific novelty of this study lies in the evaluation of the access to credit of SMEs using machine learning techniques, which consider the underlying factors, utilizing a cross-disciplinary approach by integrating mathematical and economic sciences. The study results enable a deeper understanding of SMEs' ability to borrow and modeling techniques and contribute to a clearer process of both lending and borrowing, allowing for the improvement of internal lending policies of financial institutions, and also contributes to the formation of a regulatory framework.

The paper is structured as follows. Literature review presents a basis for analyzing SMEs' access to credit modeling techniques. The Methodology, data, and research limitations section presents data and research methodology to evaluate SMEs' access to credit modeling techniques. The Results section presents the results of SMEs' access to credit modeling techniques. Section Discussion and conclusions summarizes the outcomes of this study.

Literature Review

Methods Used to Evaluate Ability to Borrow

Credit risk analysis methods comparable to pattern recognition problems, allowing algorithms to classify the creditworthiness of individual companies (Pal *et al.,* 2016; Kruppa *et al.,* 2013). Most studies examining various methods for modeling credit availability are concerned with subjects' perceived creditworthiness. Modeling credit availability is similar to assessing the financial distress of companies, as financial institutions base their lending decisions on the borrower's ability to pay future loans (Molina & Preve, 2012). Assessing credit availability is difficult for several reasons (Dastile *et al.,* 2020). One problem is multicollinearity of independent variables, where factors influencing credit availability are often interrelated and difficult to separate. Data availability may vary across markets and entities, meaning that a model that works well in one condition may not be applicable in another. Finally, there is the issue of human bias, as assessing credit availability involves interpreting decisions made by people, so the conclusions drawn can sometimes be unclear. Therefore, it is very important to carefully consider and address these factors when assessing credit availability to ensure that the resulting model is both fair and accurate.

Several studies (Cox, 1958) have evaluated accessibility to credit utilizing traditional methods such as Logistic Regression (LR) and Discriminant Analysis (DA). DA and LR are commonly used as benchmarks for comparing advanced machine learning methods, they are relatively simple and not well-suited for handling larger datasets or complex interrelations between variables (Barboza *et al.*, 2017). Traditional LR does not perform as well as advanced machine learning methods when independent variables exhibit complex nonlinear relationships. LR model may lack the predictive accuracy of more sophisticated machine learning methods. However, it provides significant advantages in terms of stability and interpretability of the variables (Bahnsen *et al.*, 2016). According to Barboza *et al.* (2017), as opposed to traditional assessment methods, advanced machine learning techniques such as Decision trees (DT), K-nearest neighbor (KNN), Random Forest (RF), Support vector machine (SVM), Artificial neural networks (ANN) method have gained popularity in recent years because they can increase accuracy and decrease bias in credit risk modeling. According to Nouri and Nikabadi (2025), a Cognitive map (CM) is not directly a machine learning technique, but it can also be used in the context of ML algorithms, particularly in tasks related to reasoning modelling, decision-making, or knowledge structure analysis. SVM can generate functions like DA. However, unlike DA, SVMs are not constrained by certain assumptions and are less limited (Cortes & Vapnik, 1995). Predicted credit rationing utilizing machine learning methods was conducted by Silva et al. (2020). Depending on the availability of data, their valuation is divided into two components: static and dynamic. It was shown that dynamic models can achieve higher accuracy than static models, but they demonstrate higher sensitivity to missing data. The inclusion of additional features does not always lead to a model with improved accuracy. Danenas and Garsva (2015) showed that SVM's accuracy could be the same as other classifiers like LR and RF. Wang *et al.* (2020) evaluated credit risk using LR, RF, kNN, DT, and Naive Bayes (NB) models, concluding that RF demonstrated the most promise regarding modeling accuracy. Trivedi (2020) noted that DT and RF classification methods provide more accurate identification of financial distress. Malakauskas and Lakstutiene (2021) notes, that the high classification accuracy of the RF method concerning credit-related issues was also confirmed by other studies, such as Khatirand and Bee (2022) and Silva *et al.*, (2020). Medianovskyi *et al.* (2023) in the study indicated that Gradient Boosting (GB) methods can perform more efficiently and accurately, providing better explainability of the model. Zhao *et al.* (2015) employed a multi-layer perceptron technique (MLP) to evaluate an Artificial Neural Network (ANN) model, which significantly outperformed other modeling algorithms. However, they identified several challenges, as MLP tends to perform poorly on unbalanced data and is difficult to interpret due to its hidden layers. Table 1 presents research on accessibility to credit and the methods employed in scientific studies.

Modern machine learning methods have many advantages; however, they also face problems. High-performing machine learning methods in strictly regulated and high-risk environments are still limited due to non-transparency to users. This situation increases the need for transparency among AI stakeholders. Decisions made by these models, according to Preece *et al.* (2018) can increase risks due to the model substantiation and inability to provide detailed explanations of their functionality. Research that analyzed the gap between the performance of machine learning models and their lack of transparency is generally classified under attitude of eXplainable artificial intelligence (XAI) (Arrieta *et al.,* 2020; Arya *et al.,* 2019). Explainability of machine learning methods is provided by Arrieta et al. (2020). Generally, highly explainable models tend to have lower accuracy, as increased complexity can hinder interpretability. Until now, it appeared that interpretability would inevitably decline with higher modeling performance. However, with the development of advanced explainability methods, this negative trend may be reversed or even completely overturned (Gunning & Aha, 2019). Table 2 highlights the performance and interpretability of various modeling methods.

Table 1

Modelling Methods Used to Evaluate Access to Credit

Modeling methods	**Researches**
Traditional methods:	
Medianovskyi *et al.* (2023), Kruppa *et al.* (2013), Malakauskas and Lakstutiene (2021), Moscato *et al.* (2021), Ariza-Garzon *et al.* (2020), Datta *et al.* (2016), Barboza *et al.* (2017), Wang *et al.* (2020), Danenas and Garsva (2015), Khatir and Bee (2022)	Logistic Regression (LG)
Barboza *et al.* (2017); Mahmoudi and Duman (2015)	Discriminant Analysis (DA statistical)
Machine learning methods:	
Danenas and Garsva (2015), Datta *et al.* (2016), Ariza-Garzon *et al.* (2020), Gu *et al.* (2025), Silva *et al.* (2020), Kruppa *et al.* (2013), Malakauskas and Lakstutiene (2021), Moscato *et al.* (2021), Trivedi (2020), Khatir and Bee (2022), Medianovskyi *et al.* (2023), Bitetto *et al.* (2023), Barboza *et al.* (2017)	Random Forest (RF)
Medianovskyi *et al.* (2023), Zhao *et al.* (2015), Barboza *et al.* (2017), Misheva *et al.* (2021), Khatir and Bee (2022), Dastile and Celik (2021), Malakauskas and Lakstutiene (2021)	Artificial Neural Network (ANN)
Gu *et al.* (2025), Datta *et al.* (2016), Khatir and Bee (2022), Wang *et al.* (2020), Trivedi (2020)	Decision Tree (DT)
Barboza *et al.* (2017), Kruppa *et al.* (2013)	Bagged-Nearest Neighbor (B-NN)
Khatir and Bee (2022), Wang *et al.* (2020), Kruppa *et al.* (2013)	K-Nearest Neighbor (K-NN)
Barboza *et al.* (2017), Bussmann *et al.* (2021), Bucker *et al.* (2022), Medianovskyi *et al.* (2023), Qi *et al.* (2021),	Gradient Boosted Machine (GBM)
Trivedi (2020), Wang *et al.* (2011), Datta *et al.* (2016), Barboza *et al.* (2017), Pal *et al.* (2016), Silva *et al.* (2020), Danenas and Garsva (2015)	Support Vector Machine (SVM)
Khatir and Bee (2022), Wang *et al.* (2020), Trivedi (2020)	Naïve Bayes (NB)

Many studies show that credit risk modeling is widespread in modern research, including complex machine learning methods. However, methods such as Random Forest, Gradient Boosted Machine, and Artificial Neural Network are difficult to interpret. They are considered less interpretable compared to the simpler Decision Tree and Logistic Regression. There is little research on the interpretability of complex machine learning methods applied to credit risk (Medianovskyi *et al.*, 2023). Therefore, when assessing the creditworthiness of SMEs, it is recommended to use different modeling methods and compare them with a benchmark. The benchmark enables objective and standardized evaluation and comparison of the performance of different methods. Statistical Discriminant Analysis and Logistic Regression, as traditional modeling methods, have been used as benchmarks for the most advanced machine learning methods. Machine learning methods such as Random Forest, Artificial Neural Network, and Gradient Boosting consistently show good assessment performance in modeling companies' creditworthiness, indicating these methods can improve accuracy and reduce bias when evaluating credit risk.

Table 2

Interpretability and Performance of Modeling Methods, Compiled from (Arrieta *et al.*, 2020; Gunning & Aha, 2019)

Performance *	*Interpretability* *	*Modeling methods*
Traditional methods:		
L	H	Logistic Regression (LG)
L	H	Discriminant Analysis (DA)
Machine learning methods:		
H	M	Random Forest (RF)
H	L	Artificial Neural Network (ANN)
L	H	Decision Tree (DT)
M	M	Bagged-Nearest Neighbor (B-NN)
M	M	K-Nearest Neighbor (K-NN)
H	M	Gradient Boosted Machine (GBM)
H	L	Support Vector Machine (SVM)
M	M	Naïve Bayes (NB)

**L-low, M-moderate, H-high*

Evaluation of Machine Learning Methods' Effectiveness

To ensure that the credit scoring methods developed for small and SMEs produce accurate results and are reliable, it is essential to apply appropriate assessment methods. Evaluating model performance aims to evaluate the model's performance with unseen data and to show problems such as overfitting or underfitting. Morrison *et al.* (2013) demonstrate that for evaluating model performance, data splitting is used when the dataset is divided into two or more subsets to evaluate and train the model. According to Gholamy et al. (2018), when developing an empirical credit accessibility model for SMEs, the majority, i.e. 80 percent, of the dataset should be used for training, and the rest for testing. This division is typically done randomly to ensure that the data represents the entire dataset, thereby preventing any kind of bias that could affect the performance of the algorithm. This algorithms helps to evaluate the capacity of the model to propagate new, unseen data.

There are different metrics, including confusion matrices, derivative metrics, and graphs, which are utilized to assess model performance (Kirasich *et al.*, 2018; Conciatori *et al.*, 2024). In this case, data splitting and performance metrics are crucial instruments for the assessment of the effectiveness of a machine learning algorithm. They ensure the eligible performance achievements of the models.

A confusion matrix, as described by Conciatori *et al.* (2024), is a table regularly utilized to assess the performance of machine learning models, especially in binary classification tasks. This matrix provides information about the expected classifications versus the actual classifications of data points. From the matrix, various evaluation metrics can be estimated. These metrics are used to describe the model's performance.

Binary classification models are generally used for performance evaluation methods. The Receiver operating characteristic (ROC) curve and the Area under the curve (AUC) are most often used (Richardson *et al.*, 2024; Wang *et al.*, 2020; Medianovskyi *et al.*, 2023; Khatir & Bee, 2022). The ROC curve shows the relationship between sensitivity and the false positive rate (FPR) at various cutoff values. To graph the ROC curve, the threshold for predicting positive cases is adjusted, and sensitivity is plotted against the FPR. A good classifier typically produces an ROC curve that is close to the upper left corner of the graph, indicating high sensitivity and low FPR. ROC-AUC is an effective measure for assessing classifier performance in cases when the distribution of the class is balanced or when the costs of false positives and negatives are equivalent. However, it may not be the best choice in cases with unbalanced distribution or where the costs of false positives and negatives differ substantially.

An effective tool for assessing the performance of classifiers in cases where imbalanced classes exist, the Precision-Recall and Average Precision (AP) metrics (Boyd *et al.*, 2013; Richardson *et al.*, 2024) are. The AP metric is very useful for evaluating performance in both information retrieval and binary classification tasks.

Methodology, Data, and Research Limitations

This section defines dependent and independent variables, the research sample that will be used in SMEs' access to credit modeling techniques testing. The techniques and methods used in modeling are presented. Limitations of the research are defined.

In the first step, a dependent indicator is determined that is used to assess SMEs' ability to borrow and the factors that determine it. To evaluate SMEs' ability to borow, this research is based on Jiménez *et al.* (2012), Cehajic and Kosak (2022), and Kirschenmann (2016), and determines that the ability of SMEs to borrow corresponds to an indicator of credit supply – the results of applications (*Outcome*), like approvals and rejections. This study focuses on the outcomes of SMEs' applications, specifically looking at the approval process and first–degree rationing. It is essential to note that the analysis is constrained to first–degree rationing (according to Kirschenmann (2016) and Jimenez *et al.* (2012).

Independent variables and research sample. To evaluate an SME company's ability to borrow, modelling algorithms and independent variables have to be selected. According to Medianovskyi et al. (2023), Malakauskas and Lakstutiene (2021), de Lange *et al.* (2022), it is crucial to consider the timing of the data collected when evaluating credit eligibility based on application outcome indicators. Properly relating this data to the underlying application is essential. To ensure accurate comparisons of modeling results across different countries, the selection of variables for empirical model estimation must consider the availability of data points for each chosen factor in all the countries being studied. According to Berger and Udell (2006), an empirical approach to credit modeling should consider both macroeconomic factors and individual application specifics. Similar to the research conducted by Karna and Stephan (2022), Angori *et al.* (2019), Cassar *et* *al.* (2015), Calabrese *et al.* (2022), Adam and Streitz (2016), and Kirschenmann (2016), this study will examine SMEs' ability to borrow in individual countries while excluding macroeconomic factors. This would help to avoid the risk of omitted variable bias that could occur if a cross-country model were used. Based on the findings of Cincikaite and Meidute–Kavaliauskiene (2023), and Molendowski and Petraskevicius (2020), there is a limited scope of studies focused on the Baltic countries, as well as a relative similarity among their economies. To address this gap, an empirical study will be conducted to assess SMEs' credit accessibility in the three Baltic countries: Estonia (EE), Latvia (LV), and Lithuania (LT). This study will analyze five years of credit data, specifically financing applications, obtained from a credit institution in these countries. Over the observed period, Estonia received the highest number of financing applications at 50998, followed by Latvia with 38924 and Lithuania with 28917. The Baltic sample is particularly relevant because all three countries (Lithuania, Latvia and Estonia) have the same main banks that provide a significant portion of all external financing.

Based on the analysis of scientific literature, 61 independent variables (factors) are selected and used to model the outcome of the financing application (*Outcome*). This includes various factors that determine the ability to obtain funding, as noted by Walsh (2010), Berger and Udell (2006), Ivashina *et al.* (2022), Fridson and Alvarez (2022), and Bitetto *et al.* (2023), and others. The list and description of independent variables for evaluating SMEs' access to credit are presented in Annex 1.

In order to obtain reliable results of SMEs' ability to borrow, modeling algorithms and benchmarks must be selected. One traditional method chosen for this analysis is Logistic Regression (LR). While LR is frequently used as a benchmark to compare with more advanced machine learning techniques, it tends to be simplistic and less effective when dealing with large data sets and complex interactions among variables (Barboza *et al.*, 2017). Regardless of its predictive accuracy, which is lower compared to some machine learning models, LR has the advantage of being more interpretable and providing stability of variable effects. LR can be served as a benchmark model to compare the results with those obtained from more advanced methods. Compared to other research such as Medianovskyi *et al.* (2023),Wang *et al.*, (2020), Barboza *et al.* (2017), Dastile *et al.* (2020), Malakauskas and Lakstutiene (2021), Khatir and Bee (2022), and Trivedi (2020), this study employs Multi–Layer Perceptron (MLP), Random Forest (RF), and Gradient Boosting (GB) for SME credit access estimation, due to their proven high discriminatory power. Gradient Boosting is especially well–suited for modeling complex, non-linear relationships and handling large numbers of explanatory variables. Compared to RF and MLP, GB is more sensitive to hyperparameter settings and at higher risk of overfitting. This makes careful tuning, through cross–validation and early stopping during training, critical to achieving optimal and robust performance. Recognizing these challenges, GB's tuning and oversight needs are explicitly addressed to ensure transparency and justify its use within this study.

The accuracy of modeling techniques will be evaluated based on the confusion matrix derivative ratios. According to Malakauskas and Lakstutiene (2021), Brereton (2021), Conciatori *et al.* (2024), Rainio *et al.* (2024), in a binary classification task, data instances are typically categorized as either positive or negative. A positive label indicates the presence of an incorrectness, abnormality, or some form of deviation, while a negative instance is consistent with the baseline. Each predicted binary label can be classified into four categories: a true positive (TP), which refers to a correctly predicted positive outcome; a true negative (TN), which is a correctly predicted negative outcome; a false positive (FP), which occurs when a negative instance is incorrectly predicted as positive; and a false negative (FN) happens when a positive instance is incorrectly predicted as negative. These classifications help assess the performance of the binary classification model.

From the confusion matrix, these measures (according to Malakauskas & Lakstutiene, 2021; Brereton, 2021; Conciatori *et al.*, 2024; Rainio *et al.,* 2024; Richardson *et al.*, 2024) are calculated:

Specificity – TN/(TN + FP);
Negative Predictive Value (NPV) – TN/(TN + FN);
Precision – TP/(TP + FP);
Sensitivity – TP/(TP + FN);
False Positive Rate (FPR) – FP/(TN + FP);
Accuracy – (TP + TN)/(TP + TN + FP + FN);
The F1-score – 2 x (Precision x Sensitivity)/(Precision + Sensitivity).

Accuracy evaluation is performed based on Precision-Recall and ROC-AUC indicators. Accuracy indicators are calculated according to Wang *et al.* (2020), Richardson *et al.* (2024), Khatir and Bee (2022), Medianovskyi *et al.* (2023).

Results

The results of the selection of independent variables are presented in Table 3, which shows the drop in accuracy at different clustering distance thresholds, choosing modeling methods based on precision and ROC-AUC.

Table 3

Accuracy Variation Across Clustering Thresholds for Different Modeling Methods

	LR	**RF**	**MLP**	**GB**
ROC-AUC				
0.00				
0.25	0.003	0.001	0.009	-0.003
0.50	0.010	0.006	0.003	-0.010
0.75	**0.000**	**0.001**	**0.000**	**0.000**
1.00	0.013	-0.010	-0.017	-0.022
1.25	0.026	0.001	0.004	-0.004
Precision				
0.00				
0.25	-0.001	0.003	0.018	-0.002
0.50	0.011	0.006	0.000	-0.009
0.75	**0.000**	**0.001**	**0.005**	**0.000**
1.00	0.019	-0.029	-0.027	-0.034
1.25	0.035	0.004	0.001	-0.006

Table 3 shows the average decrease in model accuracy using ROC-AUC and changes in precision measures, given the chosen clustering distance thresholds. The effect varies throughout different thresholds and modeling methods, and the exclusion of correlated features yields a non–uniform impact on the accuracy of the model. Across Gradient Boosting, Random Forest, and Multi–Layer Perceptron modeling methods, the method's accuracy declined markedly as the threshold increased from 0.75 to 1.00. The accuracy of Logistic Regression improved with a smaller number of variables and stood out from other modeling methods. Therefore, a representative feature vector with a clustering threshold of 0.75 is selected for model evaluation, since the drop in ROC-AUC and precision model accuracy indicators at 1.00 was taken into account.

The evaluation of SMEs' access to credit modeling techniques is performed in the case of Lithuania, Estonia, and Latvia. SMEs' ability to borrow is appreciate by using Gradient Boosting, Multi-Layer Perceptron, Random Forest, and Logistic Regression modeling methods. Independent variables from a selected representative feature vector are used to estimate the *Output*. The accuracy assessment is performed based on the ratios of the derivatives of the confusion matrix and the ROC-AUC and precision recall metrics (average precision), and the summaries are presented in Table 4.

Table 4

SME Credit Model Accuracy (By Country)

	Lithuania		Estonia		Latvia	
	ROC-AUC	**Precision (average)**	**ROC-AUC**	**Precision (average)**	**ROC-AUC**	**Precision (average)**
Random Forest (RF)	0.750	0.757	0.756	0.658	0.771	0.791
Multi-Layer Perceptron (MLP)	0.789	0.777	0.783	0.680	0.794	0.802
Logistic Regression (LR)	0.700	0.654	0.662	0.485	0.657	0.635
Gradient Boosting (GB)	**0.816**	**0.810**	**0.793**	**0.695**	**0.803**	**0.817**

Uniformly across all three countries, the best performing modeling method is Gradient Boosting. The worst performing modeling was found in the benchmark - Logistic Regression model. This model showed the lowest ROC-AUC and average precision values in Lithuania, Latvia, and Estonia. The most accurate modeling result, depending on the selected indicator, was achieved in Latvia (ROC AUC - 0.804, average precision – 0.818) and Lithuania (ROC AUC – 0.816, average precision - 0.810). However, in Estonia, the accuracy of SME access to credit modeling was the lowest, with ROC-AUC (0.796) and average precision (0.697). This is also confirmed by the results of Medianovskyi et al. (2023), which showed that Logistic Regression has competitive average accuracy but low ROC-AUC, as there is a subset of thresholds where it achieves the best accuracy among other models, but only in a very small region of recovery (true positive frequency). ROC-AUC and accuracy recovery curves (see Figure 1) are used to assess modeling efficiency at all discriminant threshold values.

The best modelling approach for assessing SME credit access was found to be Gradient Boosting. At most discriminant thresholds, the Gradient Boosting modelling approach outperformed Random Forest, Multi-Layer Perceptron, and Logistic Regression. This approach showed the highest accuracy in terms of both the overall average precision values and ROC-AUC, and at the most discriminant thresholds. The results show that in all three Baltic country methods, the Random Forest modelling approach was characterized by the highest accuracy at extreme average precision values (>0.9). When comparing the Logistic Regression method with other methods, it is consistently inefficient at all discriminant thresholds. Therefore, to evaluate the performance of the Gradient Boosting method at a single discriminant threshold value (0.5), method-specific confusion matrices and derived indicator metrics are used (see Tables 5 and 6).

The confusion matrices illustrate the performance of SMEs' access to credit predictions by comparing actual outcomes with predicted classifications of loan approval or rejection (see Table 5). The confusion matrices illustrate the performance of SMEs' access to credit predictions by comparing actual outcomes with predicted classifications of loan approval or rejection (see Table 5).

Table 5

Country-Specific Confusion Matrices for SME Credit Gradient Boosted Machine Method

	Predicted	***Approval***	***Rejection***
	Actual		
Lithuania	*Approval*	1776	477
	Rejection	874	2062
Estonia	*Approval*	4616	1007
	Rejection	1339	1995
Latvia	*Approval*	2163	701
	Rejection	1414	2684

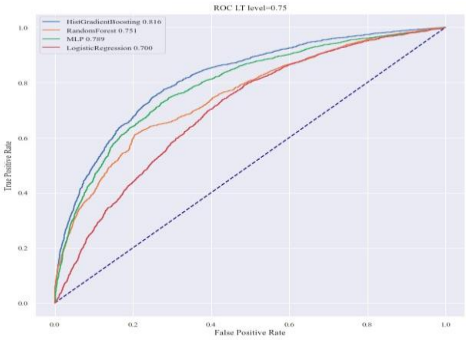
Table 6

Evaluation Results for Country–Specific Gradient Boosted Machine Method on SME Credit Access

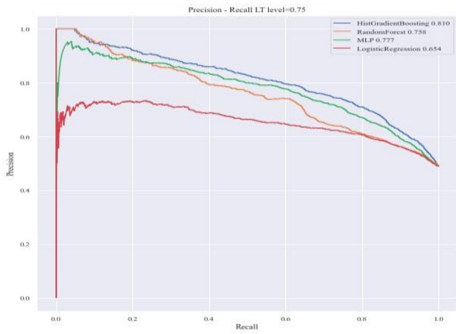
Accuracy metric	**Lithuania**	**Estonia**	**Latvia**
Specificity	0.702	0.598	0.655
NPV	0.812	0.665	0.793
Precision	0.670	0.775	0.605
Sensitivity	0.788	0.821	0.755
FPR	0.298	0.402	0.345
Accuracy	0.740	0.738	0.696
F1	0.724	0.797	0.672

Each matrix summarizes the number of true positives (correctly predicted approvals), true negatives (correctly predicted rejections), false positives (cases predicted as approvals but actually rejected), and false negatives (cases predicted as rejections but actually approved). These matrices provide detailed insight into the model's accuracy and error types across Estonia, Latvia, and Lithuania, highlighting how well the models distinguish between approved and rejected credit applications in each national context. The results indicated (see Table 6) that the model for Lithuania demonstrates the highest NPV (0.812) and specificity (0.702), suggesting a stronger tendency to identify cases as credit rationing, while still achieving a high overall accuracy of 0.740. The case of Estonia, in comparison to other countries, the highest precision and sensitivity and values, at 0.778 and 0.821, respectively, while being the lowest NPV (0.665) and specificity (0.598) values. The Estonian SME credit access model was found to be more likely to classify cases as approved, but this results in lower predictions of specificity and net present value (NPV). The lowest overall accuracy (0.696), precision (0.605) and sensitivity (0.755) values were observed for Latvia. In this case, the model is least likely to classify a event as confirmed, but it is least accurate in distinguishing predicted confirmations from actual confirmations.

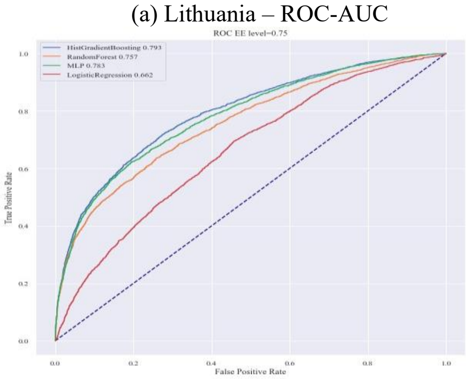
In the final stage of the study, actual rejection rates are predicted and compared over different time periods (see Figure 2). Figure 2 shows the dynamics of actual rejection rates and predicted rates for all three Baltic countries in the test dataset. Across different countries and time periods, the predicted rejection rate exhibits a tendency to both understate and overstate the extent of SMEs' access to credit. In the case of Estonia, the model substantially underestimated the actual credit rejection rate (Figure 2c), while in Lithuania it consistently overestimated the rejection rate throughout the observed period (Figure 2a). Despite these discrepancies, the model estimates depending on the specific countries generally align well with the actual levels and trends of SMEs' access to credit.



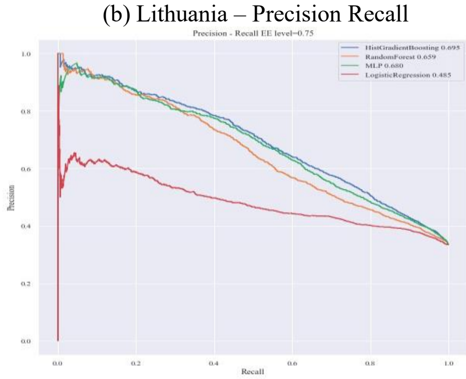
(a) Lithuania – ROC-AUC



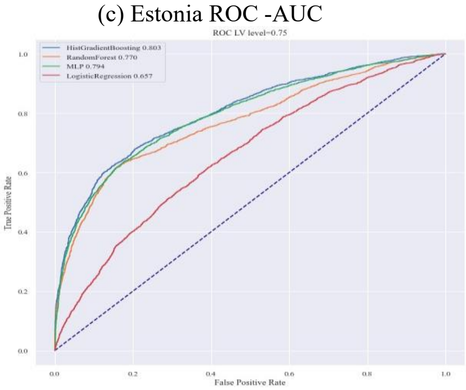
(b) Lithuania – Precision Recall



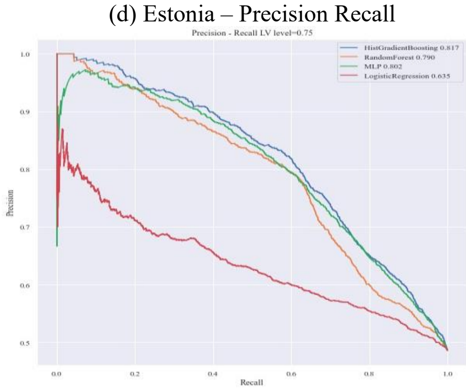
(c) Estonia ROC -AUC



(d) Estonia – Precision Recall

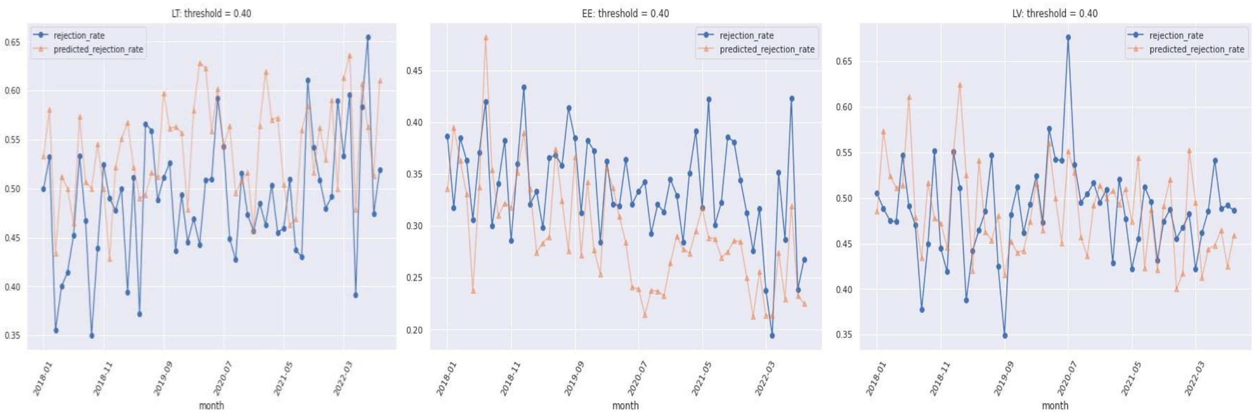


(e) Latvia – ROC-AUC



(f) Latvia – Precision Recall

Figure 1. ROC-AUC and Precision-Recall Performance Curves for Models Predicting SMEs' Credit Accessibility



(a) Lithuania (b) Estonia (c) Latvia

Figure 2. The Alignment Between Predicted Credit Access for SMEs and Observed Rejection Rates in the Test Dataset

Discussion and Conclusions

Researchers have differing opinions on which algorithms are best suited for accurately assessing creditworthiness risk. SMEs' access to credit valuation algorithms is continually being enhanced to improve accuracy. However, a review of the scientific literature reveals several algorithms that are frequently noted as significant in addressing creditworthiness risk assessment challenges. Logistic regression and Discriminant analysis models, while more traditional, maintain their accuracy in specific situations and are particularly valuable when used as a benchmark. While these methods have been regarded as the most dependable, there is a growing preference for machine learning algorithms such as Gradient Boosting, Random Forest, and Artificial Neural Networks. Advanced machine learning methods are known for their high efficiency and accuracy, ensuring robust assessments of creditworthiness using derivative ratios derived from the confusion matrix.

The results of the study showed the effectiveness of Gradient Boosting compared to other methods used in the study, including traditional Logistic Regression and advanced machine learning algorithms such as Multilayer Perceptron and Random Forest. The advanced machine learning algorithms could demonstrate high discriminatory power in credit accessibility–related models. The results are consistent with previous findings in scientific literature that machine learning methods are better than Logistic Regression in prediction accuracy. The results demonstrate that Logistic Regression retains advantages in stability and interpretability and could be useful as a benchmark (Wang *et al.*, 2020; Medianovskyi *et al.*, 2023; Khatir & Bee, 2022; Barboza *et al.*, 2017; Malakauskas & Lakstutiene, 2021; Dastile *et al.*, 2020; Trivedi, 2020). Country–level differences were observed, as the Gradient Boosting model's accuracy was different: in Estonia, it performed better in identifying credit rationing cases, while in Lithuania, it more effectively detected approved financing. This highlights the model's sensitivity to national credit allocation patterns and supports its adaptability across different markets. Its ability to incorporate a broad set of explanatory variables allows for flexible, context–specific modeling of SMEs' access to credit, making the methodology transferable and relevant for a wide range of financial institutions.

The current analysis relies on financing approvals and first–degree rationing outcomes as proxies for credit access but excludes conditional approvals (second–degree rationing) and discouraged borrowers. Incorporating these cases into future research would provide a more comprehensive view of SMEs' accessibility to credit. Although the current empirical approach does not capture these practices, the significant impact of second-degree rationing and similar discouragement strategies, especially given their potential to withhold critical financing from SMEs, warrants further theoretical discussion and exploration. More broadly, the findings confirm that access to credit and the influence of underlying factors vary across countries. This underscores the need for policymakers and financial institutions to account for national context when developing credit products and support measures. The study offers a foundation for further research and contributes to the development of data-driven, context-sensitive approaches to SME financing.

The study demonstrates the potential of machine learning techniques in improving credit risk evaluation for SMEs, addressing an important gap in the application of such tools amongst market participants and regulators. Compared to traditional models, these methods can yield more accurate and unbiased assessments of SME creditworthiness. However, their performance depends on data quality and model tuning. Sensitivity to missing data and the complexity of real-world credit decisions necessitate careful calibration and human oversight to ensure reliable outcomes.

Annexes

Annex 1.

Ratio Category for Assessing SME Access to Credit

Ratio group	**Ratio**	**Information**
Profitability	Gross margin ratio	(Net sales – Cost of goods sold)/Net sales
	Profit margin	(Net sales – Total expenses)/Net sales
	Return on assets	Net Income / Average Total Assets
	Return on equity	Net Income / Average Shareholders' Equity
Liquidity	Cash ratio	Cash/Current liabilities
	Quick ratio	(Cash + Marketable securities + Accounts receivable)/Current liabilities
	Current ratio	Current assets/Current liabilities
Activity	Asset turnover ratio	Net Sales (Revenue) /Total assets
	Receivables turnover ratio	Net sales/Accounts receivable
	Change in sales	(Sales – sales_t−1)/Sales_t−1
	Change in current assets	(Current assets – Current assets_t-1)/Current assets_t-1
Solvency Leverage	Debt to equity ratio	(Current liabilities +Long-term liabilities)/Total equity
	Debt ratio	Total Liabilities / Total Assets
	Tangible asset ratio	Tangible Assets/ Total Assets
Coverage	Debt-service coverage ratio	EBIT/Financial expenses
	Asset coverage ratio	(Tangible assets – Current liabilities)/Total liabilities
Company characteris–tics group	Size	Company's size category (EU 2003/361)
	Legal form	The legal entity type
	Age	Years
	Ownership	Private
	Location	Region, based on the EU classification of NUTS level 3 regions (NUTS 2021)
	Diversity	Female ownership percentage in the company (referencing Motta and Sharma, 2020)
	Sector	Name of the sector
	Audited	Yes, No
Relationship lending group	Point of sales	Yes, No
	Ecommerce	Yes, No
	Contracts	Count of historical financing contracts with the bank (at application time)
	Payments (Incoming Payments to Sales Ratio, %)	(atest Net Sales/Total Incoming Payment Transactions (12 months) (%)
	Duration (Bank-Company Relationship Length (days)	Application Date−Relationship Start Date
	Rejections	Yes, No
	Debt share (Bank Debt Ratio %)	(Total Liabilities/Debt Held in Banks)×100
	Debit cards	Yes, No
Transaction lending group	Defaults on obligations Owner's defaults on obligations	
	External overdues debt number over 2 years External overdue debt duration over 2 years External overdue debt amount over 2 years	
	Internal overdue debt number over 2 years Internal overdue debt duration over 2 years Internal overdue debt amount over 2 years	
	Owner's external overdue debt number over 2 years Owner's external debt duration over 2 years Owner's external amount of overdue debts over 2 years	
	Owner's internal overdue debt number over 2 years Owner's internal overdue debt duration over 2 years Owner's internal amount of overdue debts over 2 years	
Product type	Trade finance, Cash-flow loans, Leasing, Credit Cards, Asset-based loan	

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This study would not have been possible without the contribution of Swedbank AB. Portions of this article are derived from the doctoral dissertation of Aidas Malakauskas (2023) at Kaunas University of Technology. The current manuscript has been enhanced through collaborative work with the co-authors. The dissertation is available from the KTU Institutional Repository.

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