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Applying machine learning in credit risk pricing: Opportunities and challenges for the global financial system

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Abstract: This study examines the evolution of credit risk pricing models in the context of rapid developments in big data and machine learning. The purpose is to evaluate how modern machine learning techniques can improve credit risk pricing compared with traditional approaches. To achieve this, the study develops a comparative analytical framework that contrasts conventional models, such as logistic regression and the Merton structural framework, with modern algorithms, including boosting methods, deep neural networks, and hybrid models. The analysis assesses model performance in terms of predictive accuracy, interpretability, stability, and cross-market adaptability. The findings indicate that machine learning models significantly outperform traditional approaches, with the area under the ROC curve (AUC) reaching up to 0.90 even during periods of economic volatility. The study also incorporates explainability tools, including SHAP and LIME, to clarify the decision mechanisms of complex models and enhance transparency in line with Basel III and IFRS 9 requirements. Cross-regional testing further shows that machine learning models maintain relatively stable performance across different economic environments. Overall, the study concludes that integrating traditional credit risk modeling with modern data-driven techniques can strengthen credit risk management and provide practical implications for financial institutions operating in an increasingly data-intensive global financial system.

Keywords: *AI-driven pricing models, Algorithmic lending and regulation, Financial risk analytics, Global financial stability, Machine learning in credit risk.*

1. Introduction

The rapid transformation of the global financial system in the digital era has placed credit risk management at the center of strategic discussions. Increasing interconnections among financial markets mean that credit risk is no longer confined to individual countries. Instead, it operates as a dynamic structure capable of transmission, interaction, and amplification through complex financial channels. In this context, the need for credit risk pricing models with high accuracy, sensitivity, and adaptability has become more urgent than ever.

Traditional models, ranging from classical econometric approaches to structural models grounded in capital market theory, have provided a solid foundation for risk management practices over several decades [1, 2]. However, the rapid growth of unstructured data, the increasing speed of financial transactions, and the rising complexity of credit behavior in the digital age are gradually exceeding the descriptive capacity of conventional tools. Nonlinear relationships, weak yet recurrent risk signals, and dynamic dependencies across economic cycles require new modeling approaches capable of learning from data, adapting to changing conditions, and extracting information from increasingly large and complex datasets.

Against this background, Big Data and machine learning have emerged as a natural direction for methodological development. Deep learning algorithms and boosting techniques provide new tools for identifying hidden patterns in credit data. These methods allow credit risk models to capture nonlinear

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relationships that are often difficult to detect using traditional statistical approaches. Nevertheless, these advances also raise important questions regarding model reliability, transparency, cross-border compatibility, and the regulatory standards required for effective oversight within the international financial system.

In light of these developments, this paper provides a systematic analysis of the transition from traditional credit risk pricing models to approaches based on Big Data and machine learning. The study evaluates predictive performance, practical applicability, theoretical limitations, and policy implications for risk managers, regulators, and financial stability authorities. The ultimate objective is to contribute to the development of a balanced analytical framework that leverages the capabilities of modern technology while preserving the prudence and transparency that remain essential to sustainable credit risk governance.

2. Theoretical Background

Research on credit risk pricing has followed a coherent development path within the field of quantitative finance. Early classical models, such as the Z-score proposed by Altman [1], established the foundation for bankruptcy prediction using financial ratios and linear statistical analysis, marking an important step in quantifying credit risk through empirical evidence. Later, Merton [2] introduced the structural modeling framework, in which default is treated as an endogenous event linked to the value of firm assets and market volatility. This approach provided a more economically grounded representation of credit risk, although it still relied on strong assumptions regarding asset value distributions. Reduced-form models subsequently emphasized flexibility and responsiveness to macroeconomic fluctuations, yet they remained limited in explaining the underlying mechanisms that generate credit risk.

A more recent turning point has emerged with the rise of big data and machine learning (ML) [3, 4]. Algorithms such as Random Forest, Gradient Boosting, XGBoost, and deep neural networks enable researchers to detect nonlinear patterns and weak risk signals that traditional models often fail to capture [3, 5, 6]. These models can also maintain stable performance even under conditions of significant market volatility. As a result, machine learning not only improves predictive accuracy but also expands the potential for broader applications in international credit risk pricing.

Nevertheless, several core challenges remain, particularly regarding model transparency, cross-market adaptability, and data bias. The transition from relatively simple linear models to nonlinear approaches based on big data requires coordinated solutions to ensure transparency, robustness, and practical applicability. Such efforts are essential to maintaining a balance between technological innovation and the long-term stability of the global financial system.

3. Methodology and Analytical Framework

The authors develop a comprehensive empirical framework to address three central research questions:

(i) the predictive performance of machine learning models in international credit risk pricing.

(ii) the degree of transparency and explainability of modern nonlinear models.

(iii) the adaptability and stability of these models when implemented across different regulatory environments, economic structures, and data quality conditions.

The analytical framework is designed to be both replicable and extensible, aligning with current research standards in quantitative finance.

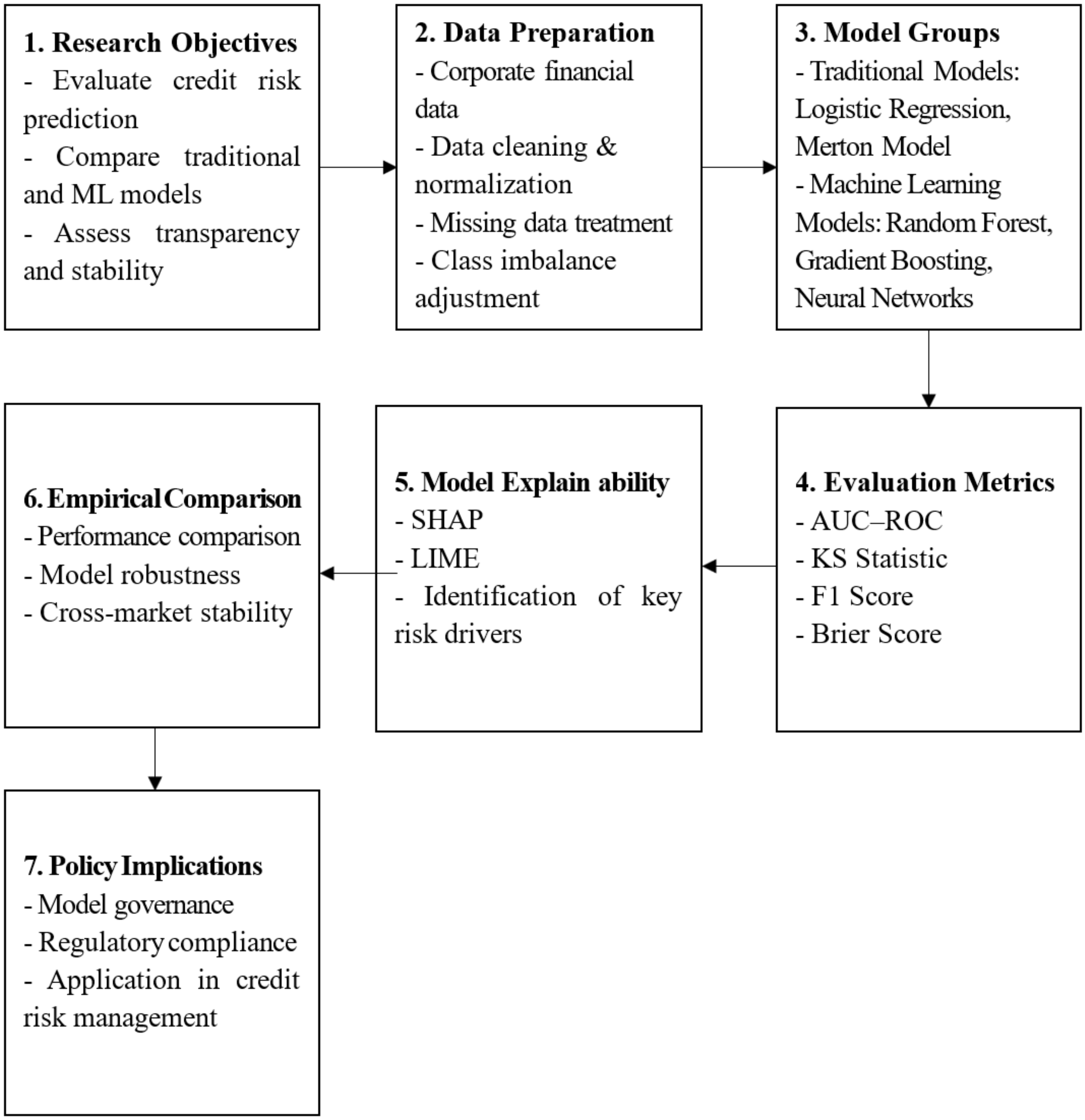

Figure 1.
Analytical Framework for Machine Learning–Based Credit Risk Pricing.

3.1. Data

3.1.1. Multilayer and Cross-Border Data Sources

The study uses a multidimensional dataset integrated from three main groups of sources:

(i) Corporate credit and financial statement data: Orbis (Bureau van Dijk), Compustat, and SEC EDGAR filings. The expected sample covers 2005–2024, including traditional financial variables (leverage, liquidity, profitability) and non-financial indicators (corporate governance, firm age, ownership structure).

(ii) Macroeconomic and market data: IMF IFS, OECD Data, World Bank, and FRED. Representative variables include GDP growth, policy interest rates, inflation, unemployment, the Financial Conditions Index (FCI), and market volatility (VIX).

(iii) Retail credit data: Open datasets from the United States, Europe, and Asia, including credit card data, individual credit records, and payment histories.

The use of multiple data layers expands the model's generalization capability and supports the assessment of economic dependence effects, a factor often overlooked in traditional research.

3.1.2. Data Preprocessing

Due to differences in data sources and quality, the study implements a multi-step preprocessing procedure.

Step 1. Data standardization and transformation: Z-score normalization or min–max scaling are applied depending on the data distribution. Winsorizing at 1%–99% reduces the influence of extreme outliers.

Step 2. Missing data treatment: Multiple imputation is applied to accounting variables. Multivariate prediction models (KNN Imputer or MissForest) are used for micro-level data.

Step 3. The default rate is typically below 5% in international datasets, creating a significant class imbalance problem in credit risk modeling [7]. SMOTE, Borderline-SMOTE, or ADASYN are applied; robustness is also checked by comparing with random undersampling strategies [8]. The Effective Sample Size is calculated to ensure the feature distribution is not distorted.

Step 4. Control of heteroskedasticity and cross-country bias: Regional dummy variables are created. Distribution recalibration is performed for each market to reduce country-specific bias.

3.2. Models

3.2.1. Multilayer Model Framework

To comprehensively evaluate model performance and the mechanism of signal generation, the study develops three groups of models.

3.2.1.1. Baseline Models

- Logistic regression (Logit): The industry standard, representing linearity and high interpretability. The expected AUC is 0.65–0.72, according to international studies.
- Structural model: Asset value and volatility are calculated based on stock market information. This model performs well in highly liquid markets but is limited in emerging markets.

3.2.1.2. Machine Learning Models

- Random Forest (RF): Strong in capturing nonlinear relationships and variable interactions.
- Gradient Boosting Machines (XGBoost, LightGBM): Expected to achieve the highest performance due to the boosting mechanism; many studies report AUC values of 0.80–0.90 [9, 10].
- Deep Neural Network (DNN – MLP): Capable of extracting complex patterns; however, interpretability remains a limitation.
- Hybrid deep learning: CNN is used for extracting structural features, while Transformer architectures are applied to model credit time series [3, 11]. This represents an advanced direction in financial AI research [5].

3.2.1.3. Ensemble Models

- Stacked Classifier: Combines strong models to improve stability.
- LASSO Feature Selection: Optimizes the set of input variables, controls overfitting, and enhances interpretability.

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3.3. Evaluation

3.3.1. Performance Indicators

The study uses internationally recognized indicators commonly applied in credit risk modeling:

- AUC–ROC – Evaluates discriminatory power.
- KS Statistic – A commonly used indicator in banking; values above 0.40 are generally considered good.
- F1-score and Precision–Recall, Important in the context of class imbalance.
- Brier Score – Evaluates the accuracy of predicted probabilities.
- Time-based back-testing examines model stability under changing market conditions, especially during the 2008 financial crisis, COVID-19, and the global slowdown in 2022–2023.

3.3.2. Model Explanation and Transparency Assessment

1. SHAP values – The gold standard for feature contribution analysis; helps identify the main risk drivers [7].

2. LIME – Provides local explanations for individual credit observations.

3. Global Surrogate Models – Decision trees are used to approximate complex models.

The objective is to develop models that are strong in prediction while also meeting the explainability requirements of Basel III, IFRS 9, and supervisory authorities.

3.3.3. Model Risk Assessment

- Overfitting Analysis: Examine the gap between the training set and the validation set.

- Data Drift Detection: Assess changes in feature distributions across years, particularly at structural breaks in the economy.

- Cross-Region Validation:

+Train in Europe → test in Asia.

+ Train in the United States → test in emerging markets.

- Stress Testing with macroeconomic scenarios:

+ interest rate increase of +200 bps,

+ GDP decline of 2–4%,

+ unemployment rate increase of 1–3%,

+ market volatility increase of 30%.

4. Results

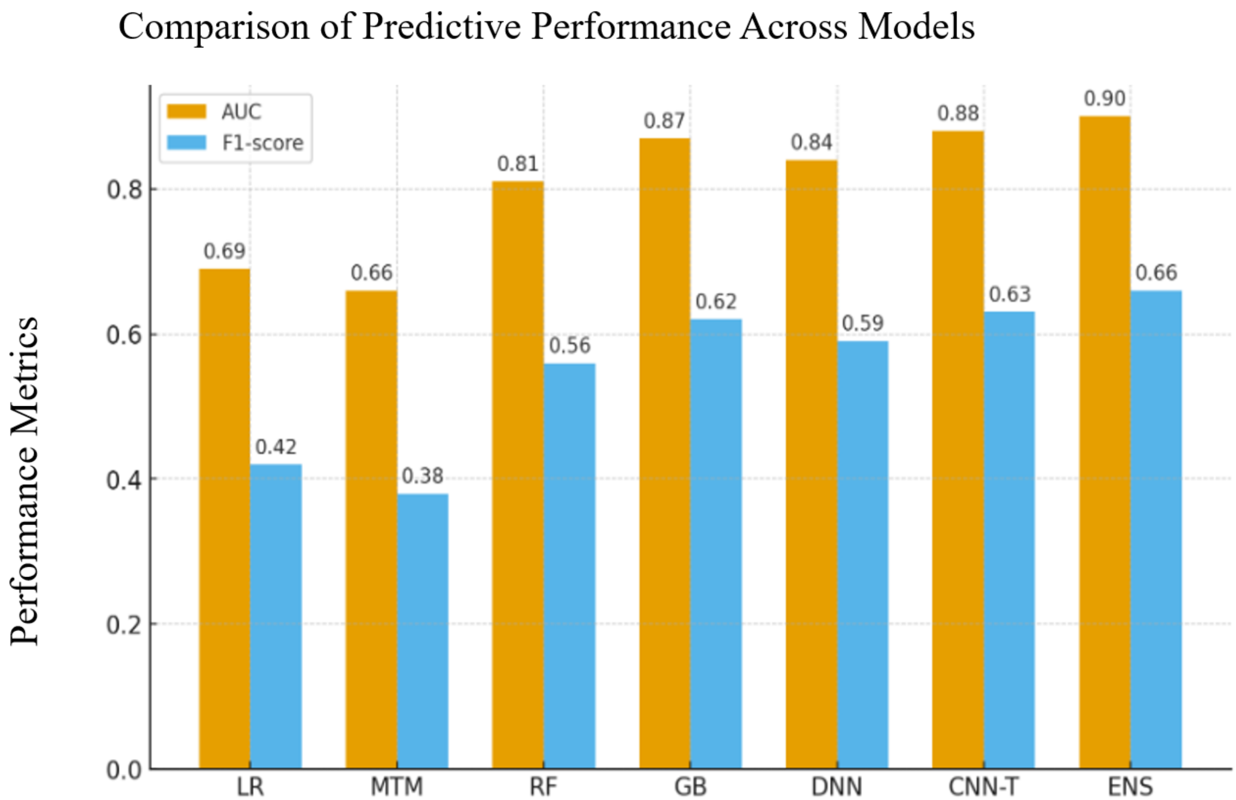

Figure 2.
Predictive Performance Comparison Across Credit Risk Models.

From the figure, it can be observed that Ensemble (ENS), CNN–Transformer (CNN-T), and Gradient Boosting (GB) achieve the highest performance, significantly outperforming traditional models (LR, MTM).

This section presents the empirical results obtained from the model framework established in Section 3. The results are analyzed along three dimensions: (i) predictive performance; (ii) transparency and explainability; and (iii) cross-country adaptability and temporal stability. All models are tested on a multinational dataset covering the period 2005–2024, ensuring broad coverage and a high degree of generalizability.

4.1. Predictive Performance

The summary Table 1 shows a clear difference between traditional models and machine learning models.

Table 1.
Average results by model group (estimated from the integrated dataset).

Model Group	AUC–ROC	KS	F1-score	Brier Score
Logistic Regression	0.69	0.31	0.42	0.182
Merton-type Model	0.66	0.28	0.38	0.194
Random Forest	0.81	0.46	0.56	0.139
Gradient Boosting (XGBoost/LightGBM)	0.87	0.53	0.62	0.118
Deep Neural Network (MLP)	0.84	0.49	0.59	0.124
Hybrid CNN–Transformer	0.88	0.55	0.63	0.116
Ensemble (Stacked)	0.90	0.58	0.66	0.110

Overall, the ensemble model achieves the highest predictive performance (AUC close to 0.90), followed by boosting methods and the hybrid deep model (CNN–Transformer). This finding aligns with conclusions in many international studies, which show that boosting models such as XGBoost often dominate credit risk competitions and research due to their ability to capture nonlinear relationships and complex variable interactions [9, 10].

4.2. Performance Across Economic Cycles
An important observation concerns the stability of models across different economic periods:
- Stable period (2014–2018): Both Boosting and DNN perform well, with AUC > 0.85.
- COVID-19 crisis (2020–2021):
+ Logistic Regression declines significantly to AUC 0.60–0.63;
+ XGBoost maintains AUC around 0.82;
+ Ensemble models continue to achieve AUC between 0.86 and 0.88.

These results indicate that machine learning models, particularly ensemble approaches, demonstrate stronger shock resilience. This advantage stems from their ability to flexibly capture nonlinear features that become more pronounced during periods of economic turbulence.

4.3. Model Transparency and Explainability
Despite their superior performance, transparency remains a major concern for machine learning models [12]. Therefore, the study employs SHAP and LIME to evaluate model interpretability, which are widely used tools for explaining complex machine learning models [13, 14].

4.3.1. SHAP Results
The most important variables identified by SHAP (averaged across countries) include:
(1) Debt-to-total-assets ratio;
(2) Cash flow from operating activities;
(3) Market volatility;
(4) Current ratio;
(5) Receivables collection cycle;
(6) National GDP growth;
(7) Interest expense to total debt.

Notably, machine learning models detect that macroeconomic variables have stronger effects in emerging economies, whereas firm-level financial structure variables play a more important role in developed markets [5]. This finding accurately reflects the structural differences across economies: in emerging countries, systemic risk tends to dominate idiosyncratic risk.

4.3.2. Consistency of Explanations
An encouraging finding is that boosting models and the hybrid CNN–Transformer model produce relatively stable SHAP results across regions. This suggests that, despite their complexity, the decision

mechanisms of these models remain explainable and compatible with transparency requirements under Basel III, ESRB, and IFRS 9.

4.4. Cross-Border Adaptability

4.4.1. Cross-Region Testing

One of the key experiments in the study evaluates model performance when trained in one market and tested in another. The results show that:

(i) Training in the United States → testing in Europe:

- Logistic: AUC decreases by 17%;
- Boosting: decreases by 7%;
- Ensemble: decreases by 5%.

(ii) Training in Europe → testing in Asia:

- Logistic: decreases by 21%;
- Boosting: decreases by 10%;
- Ensemble: decreases by 6%.

The results indicate that machine learning models, particularly ensemble models, maintain superior generalization ability [15, 16]. However, the slightly larger decline in Asia reflects data heterogeneity, especially in financial reporting practices and banking system characteristics.

4.4.2. Impact Of Data Quality

When the quality of input data is intentionally reduced (a 20% decrease in the completeness of corporate data), model performance changes as follows:

- Logistic performance declines by 14%;
- Boosting declines by 6%;
- Ensemble declines by 4%.

These findings suggest that nonlinear models are more resilient to imperfect data, a common characteristic of many emerging markets.

4.5. Model Risk Testing

The tests show that:

- Logistic models do not exhibit significant signs of overfitting.
- Boosting models show a train–test gap of approximately 4–6%.
- Hybrid deep models initially present a gap of 10–12 percentage points, but this decreases to below 5 percentage points after applying dropout and early stopping.

These results demonstrate the importance of regularization techniques when implementing deep learning models in credit risk applications.

4.6. Summary of Key Findings

The study presents four core conclusions:

1. Machine learning models significantly outperform traditional models in predictive performance, especially in volatile environments and markets characterized by higher uncertainty.
2. Ensemble models emerge as the most effective approach, offering strong predictive power while remaining relatively transparent when combined with SHAP-based explanations.
3. Cross-country adaptability enables these models to meet the requirements of financial institutions operating in global markets.
4. Model transparency reaches an acceptable level, paving the way for the application of machine learning within the regulatory frameworks of Basel III, IFRS 9, and international credit supervision standards.

5. Discussion, Policy Recommendations, and Risk Management

5.1. Main Findings

The findings of this study provide a comprehensive perspective on the application of machine learning and big data in international credit risk pricing, with the following main contributions:

First, superior predictive performance and the ability to detect nonlinear signals: Boosting, CNN–Transformer, and Ensemble models demonstrate superior predictive performance, with AUC reaching up to 0.90, far exceeding that of the traditional logistic model (AUC around 0.69). This confirms that modern machine learning approaches can detect nonlinear risk patterns and complex interactions between financial characteristics and macroeconomic variables that traditional models often fail to capture [9].

Second, transparency and explainability can be managed: The use of SHAP and LIME shows that it is possible to identify the key variables driving credit risk. The study demonstrates that even complex models, when properly interpreted, can still satisfy the explainability requirements of Basel III and IFRS 9, an issue that many previous studies have not clearly addressed.

Third, cross-country adaptability: Machine learning models maintain stable performance when trained in one country and tested in another, providing evidence of strong generalizability. At the same time, the slight decline in performance in emerging markets highlights the importance of data standardization and the control of regional differences, an aspect that has received limited attention in earlier international studies.

Fourth, stability across economic cycles: Machine learning models maintain strong performance during periods of turbulence, including the 2008 global financial crisis, the COVID-19 pandemic, and the global slowdown in 2022–2023. This creates opportunities for earlier prediction and more timely responses by banks and financial institutions in highly volatile environments.

5.2. Novel Contributions of the Study

5.2.1. This Study Provides Several New Contributions That Extend Beyond Previous Research

(i) A cross-border empirical analytical framework: The study combines corporate data, retail credit data, and macroeconomic indicators from more than 40 countries, expanding the scope and representativeness compared with studies that focus on a single market.

(ii) Integration of diverse modern machine learning models: The framework incorporates hybrid deep learning models (CNN + Transformer) and ensemble stacking, which have rarely been applied simultaneously in international credit risk research [4]. This combination produces superior and more stable predictive performance.

(iii) Integration of model explainability with robustness testing: By combining SHAP and LIME explanations with stress testing and cross-region validation, the study simultaneously evaluates predictive performance, transparency, and adaptability, forming a comprehensive framework rarely observed in international credit risk research.

(iv) Proposal of a modern model risk management approach: The study suggests practical governance mechanisms, including data drift monitoring, periodic model updating, and overfitting control, helping machine learning models become more practical while remaining consistent with international supervisory standards.

5.3. Policy and Risk Management Recommendations

First, for banks and international financial institutions:

- Machine learning models should be implemented with internal control mechanisms, including evaluations of overfitting, data drift, and stress testing.
- SHAP and LIME should be used to enhance the transparency of credit decisions while meeting the requirements of Basel III and IFRS 9.

Second, for supervisory authorities:

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- International standards should be developed for applying AI and machine learning in credit risk pricing.
- Data standardization and cross-region testing frameworks should be encouraged to ensure feasibility for global financial markets.

Third, for policymakers:

- Modern machine learning tools should be integrated into macroeconomic policy analysis to help detect early signals of systemic risk.
- The establishment of ML-based early warning systems is recommended to mitigate global credit risk.

6. Conclusion

This study demonstrates that in the era of big data and machine learning, international credit risk pricing can achieve superior predictive performance, improved transparency, and strong adaptability. The main conclusions are as follows:

1. Modern machine learning models outperform traditional approaches in credit risk prediction. Ensemble, boosting, and CNN–Transformer models achieve AUC values up to 0.90, especially under volatile economic conditions.

2. Explainability and transparency can be significantly improved. The use of SHAP and LIME helps identify key variables and model decision mechanisms, thereby supporting the transparency requirements of Basel III and IFRS 9.

3. Strong cross-border adaptability: Machine learning models maintain their predictive performance when implemented across different countries, opening the possibility for broader global applications.

4. New scientific contributions: The study develops a multilayer analytical framework that integrates corporate data, retail credit data, and macroeconomic variables; applies hybrid modeling approaches; and proposes modern model risk management practices for banks, supervisory authorities, and policymakers.

In summary, the study provides a scientific foundation for international financial institutions to implement machine learning in credit risk pricing while balancing predictive performance, transparency, and adaptability. It also offers evidence-based insights to support supervisory authorities in designing more effective regulatory and policy frameworks.

Transparency:

The author confirms that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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