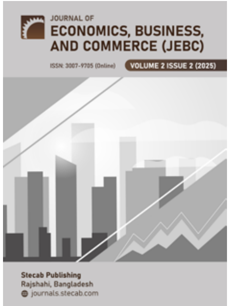

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Research Article

Nonlinear Dynamics in Export Payment Risk: A Gradient Boosting and SHAP-Based Explainable AI Model

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About Article

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ABSTRACT

Timely repatriation of export value after export is a global challenge. Some determinants such as the payment behavior of the importer, the liquidity and health of the foreign bank, and the country risk of the importer can provide early signals about whether the export value will be repatriated on time. In this study, we have classified how the export value is repatriated based on some historical data such as on-time, early, and delayed. Then, we have looked at the scores using machine learning algorithms such as Logistic Regression, Random Forest, Gradient Boosting Machine (GBM), and Artificial Neural Network (ANN). In the study, we found empirical superiority of GBM, which achieved a macro-averaged AUC-ROC of 0.915 and a Recall of 85.4%. According to the SHAP (SHapley Additive exPlanations) predictor, 55.3% of it depends on the payment behavior of the importer. The study also shows that there is a significant non-linear behavior pattern between non-compliant bank profiles and high country risk of the importer. By adding Explainable AI (XAI), this model can be made more transparent and interpretable supporting practical, risk-based decisions such as adjusting pre-shipment finance limits, determining post-shipment tenors, or initiating early export bill lien actions. As a result of this study, banks can be proactive in export bill liens, pre-shipment finance, post-shipment tenors and maintain compliance easily.

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1. INTRODUCTION

For the economic growth of an export-led economy, international trade plays a dynamic role. A major enabler of this growth is the fluid execution of exports and timely realization of export proceeds. When importers do not clear export bills in time or default altogether, the exporters, banks, and financial intermediaries are exposed to liquidity risk, credit risk, and operational uncertainty (BIS, 2014; "Trade finance: developments and issues," 2014). Global supply chain disruptions, volatile macroeconomic conditions, and geopolitical stability fluctuations in recent times have enhanced these risks, and the correct prediction of export bill settlement outcomes has become increasingly important for trade financiers, exporters, and policymakers. Historically, risk assessment in export finance has depended on qualitative judgments of country credit ratings, importers' payment history, and bank reputation. Although helpful, such techniques tend not to incorporate intricate, non-linear variable relationships, e.g., the interaction between importer country risk, banker stability, and payment history on settlement delay or default probability. The introduction of machine learning (ML) and artificial intelligence (AI) techniques has introduced the use of big data, dynamic feature engineering, and predictive analytics to financial risk modeling in order to enhance forecast accuracy. The latest studies demonstrate that machine learning-based credit risk models are superior to traditional linear regression models in recognizing high-risk trade credit firms based on attributes such as trade credit history and financial ratios (Liao, M., Jiao, W., & Zhang, J. ,2025). Predictive models for export credit insurance claims reveal that ensemble techniques such as Random Forest, XGBoost, or LightGBM are more accurate in predicting the claim probability than baseline models (Krummaker, 2020). In spite of these advances, there is a research gap with regard to export bill settling modeling. First, most of the extant research concentrates on aggregate trade credit or insurance claims, rather than the precise incidence of export bill settlement.

Second, most of the models leave out important contextual variables, including country-level economic data (e.g., GDP growth, currency volatility), characteristics of the importer's home bank (e.g., bank size, regulatory compliance), and intricate patterns in payment behavior (e.g., previous delays, partial payments). Explainability and interpretability of AI models in this domain tend to be low, which can discourage banks and trade finance institutions that need transparency for risk management and compliance from adopting them. This study fills these gaps by coming up with an AI-based predictive modeling method for export bill settling. The research has three distinct objectives: to construct and compare a number of machine learning models (e.g., logistic regression, random forest, gradient boosting, and artificial neural networks) in the prediction of the timeliness of export bill payment, categorizing results as on time, delayed, or default; to identify and estimate the relative importance of predictor variables such as importer country risk, banking attributes, and historical payment history; and to examine model interpretability and stability, ensuring results are applicable to practical trade finance contexts. Economically, the study adds value by enabling banks and exporters to anticipate high-risk transactions earlier, allowing more efficient allocation of trade finance capital, reducing potential default-related losses, and lowering compliance and monitoring costs through more targeted risk segmentation. This study contributes theoretically and practically.

1.1. Research Questions

1. To what extent can machine learning models based on AI predict the results of export bill settlements (Early, On-Time, Delayed/Default) better than the conventional linear econometric models?
2. To what extent can explainable AI (XAI) procedures such as SHAP raise both the usability and control acceptability of predictive frameworks in trade finance risk evaluation?
3. Which predictive variables, such as, importer country risk, bank variable and importer payment behavior, have the greatest impact on the expediency of the export bill settlement?

1.2. Research Objectives

1. To model and compare the diverse machine learning models (Logistic Regression, Random Forest, GBM and ANN) to predict the possibility of an export bill settlements and to measure the predictive accuracy and predictive strength.
2. To determine and measure the relative value of multi-level risk factors, that is, importer country characteristics, bank credibility and historical payment behavior in settling price predictably.
3. To make explainable AI approaches (e.g., SHAP and PDP) to enhance model transparency and interpretability, make the models usable and auditable by financial institutions and regulators.

2. LITERATURE REVIEW

2.1. Overview of Export Bill Settlements in Trade Finance

Export bill settlement plays a key role in the global economy by incorporating trade relations and financial conversion. Liquidity is determined by timeliness of payment which defines the working capital efficiency and the general competitiveness of the exports. (Miller & Rojas, 2019; Lessmann et al.,2015) explains that the perception of risk by the exporter about the importer in the country they are dealing with and institutional reliability affects how far the exporter will give them credit and how they make payments. The conventional trade finance structures have focused on creditworthiness and macroeconomic variables and are not working to capture dynamic behavioral impacts on the performance of settlement. More recently, hybrid AI–XAI frameworks have been adopted in financial risk modeling, where learners are paired with interpretation tools such as SHAP or LIME to capture non-linear patterns while maintaining transparency. Studies in credit risk scoring, banking default prediction, and fraud monitoring (Lessmann et al., 2015; Liao et al., 2025; Zhang & Zhu, 2022) demonstrate that combining machine learning models with explainability techniques improves both predictive accuracy and regulatory acceptability. However, these hybrid approaches have not been applied specifically to export bill settlement, creating a clear methodological gap that this study aims to address.

2.2. Determinants of Settlement Delays

Various researches point out that the three most predominant determinants of export delays in payment are the importer behavior, banking efficiency and country risk.

• *Importer Country Risk:* According to the studies made by Eaton and Kortum (2018), country economic variability and exchange rate instability are the factors that contribute greatly to cross-border payment reliability. Political instability, trade restrictions and regulatory bottlenecks also cause delay risk (World Bank, 2022).

• *Banking System Efficiency:* Ghosh and Das (2021) discovered that the inner clearance mechanisms of banks, their global network power and complying procedures affect the time of settlement, particularly when using Letters of Credit (LC) (Zhang & Zhu, 2022; OECD, 2021).

• *Payment Behavior:* The behavioral finance school of research (Thaler and Sunstein, 2008) proposes that behavioral consequences of organizational conduct, trust relationship, and prior compliance trends are good predictors of financial timeliness. Eg, repeat patterns are observed in importers who have a history of late payments and this indicates the persistence of behavior (Chatterjee,2022; Boztepe er al.,2025).

2.3. An integrated AI- XAI framework attached to the study's goals

Hybrid modeling methods combing transparent tree-based ensemble with explainable post-hoc explanation procedures have therefore gained traction in the financial risk spaces. As per this research purpose, a Tripartite theory model is recommended to cover the complexity of the export bill settlement. The model synthesizes:

(1) Trade Risk Theory: to describe payment probabilities and default under asymmetric information;

(2) AI-driven predictive analytics approach: Need to be insightfully adopting complex data patterns and feature dependencies; and

(3) Behavioral Risk Framework: It inputs the necessary human and institutional behaviour of trust, past behaviour, and contextual norms.

The likelihood of a successful export bill settlement is a function of multiple dimensions. It is primarily dependent on the credibility of the facilitating bank, the importer's country stability, and the importer's track record of payments. Furthermore, we propose that these relationships are not direct but are mediated by the interplay of the behavioral and structural factors delineated in our theoretical model.

2.4. Conceptual Framework

The conceptual model puts Export Bill Settlement Outcome as the dependent variable and three broad groups of predictors as independent variables, namely, Importer Country, Importer Bank, and Payment Behavior (Darwish, 2023; Nguyen et al., 2023). These variables combine with financial and time related factors (Bill Amount, Currency, Issue Date, Maturity Date, Realized Date) to affect the probability and the amount of delay (Xu, 2024).

The framework is based on the assumption that the AI models can be trained to comprehend the patterns on historical data on transaction outcomes and categorize them into three major group of outcomes: settlement (Molnar, 2022; Boztepe et al.,2025).

1. Early Settlement (before maturity)
2. On-Time Settlement (under the range of tolerance)
3. Delayed Settlement (settlement after maturity)

3. METHODOLOGY

The research design embraced in this study is quantitative modeling because it aims at establishing an AI based predictive predictor that aims to develop, compare, and validate various Machine Learning (ML) models to foresee the promptness of export bill payments. The entire research process is objective-driven; thus, methodology seeks to translate the three interconnected underpinning theories, which are the Trade Risk Theory, the AIDriven Predictive Modeling Framework, and the Behavioral Risk Framework, into empirical robust analysis. In particular, the methodology used in the study closes the identified research gap by integrating cross-level predictors and stressing the model explainability to enhance the possibility of utilizing the outcomes in trade finance. The dataset used in this research was obtained directly from the Trade Finance Operations Division of United Commercial Bank PLC, Dhaka, Bangladesh, consisting of five years of verified export bill transactions. This proprietary institutional dataset ensures high granularity and accuracy while providing a realistic ground for empirical validation.

3.1. Research Aims and Methodology

There are three original study objectives:

1. Model Building and Testing: Building and testing numerous machine learning models predicting the multi-class outcome of export bill settlement: "Early", "On-Time", and "Delayed".

2. Estimation of Variable Importance in Prediction: Establishing and estimating the importance of differential predictor variables representing importer country risks, bank characteristics, and their past transaction history.

3. Model Interpretability and Stability: Assessing the performance of the top models in terms of their interpretability compliance with regulation, and stability.

3.2. Philosophy of Data and Feature Engineering

The data structure is organized to consider the three-stage risk of export bill settlement. We have organized this in a way that reflects the complexity and non-linear relationships between the layers.

3.2.1. Features Conceptualization

Features conceptualization is based on the following pillars:

• *Behavioral Risk Framework (Micro-Level):* It is possible to analyze the dynamics, probability of late payment, average duration and dispersion from the importer's past payment records. Through which it is possible to identify complex patterns of payment behavior beyond binary payment history.

• *Trade Risk Theory (Macro and Meso Levels):* This framework takes into account the institutional characteristics of the importer's bank (e.g. financial liquidity, payment switches, credit rating and digital capabilities) and some macro-level variables of the importing country such as political instability, inflation, and reserve deficit.

• *AI-Based Predictive Modeling Framework:* Such a framework examines interactions between variables at all levels (such as high-risk countries and robust banking counterparties) to make it easier to identify non-linear relationships between them, which is not possible in conventional models.

3.2.2. Specification of the Target Variable

The timely settlement of the dependent variable can be called a multi-class categorical response based on settlement delay. Such a classification should have the ability to easily identify "on time", "early settlement" and "delayed" payments. In an effort to enhance granular risk score, the 'Delayed' segment will further be split into risk categories (e.g., short delay, moderate delay, and default/extreme delay) to enhance best-in-class model effectiveness in supporting differentiated provisioning and risk management.

3.2.3. Data Preprocessing and Handling of Imbalance Preprocessing

These involve regular operations such as imputing missing data using suitable imputation techniques, scaling continuous features to ensure equal weighting of differently scaled features for example the bill amount versus currency volatility, and encoding high-cardinality categorical features for example Importer Country and Bank to get the data ready for use by different ML algorithms. Significantly, as due to the rare but vital occurrence of extreme delays or defaults, the data will have important class imbalance. During training, techniques such as stratified sampling, cost-sensitive learning weighted loss functions, and advanced resampling methods for example synthetic minority oversampling will be utilized to combat model bias in favor of the large 'On Time' class.

3.3. Model Selection, Training, and Evaluation

3.3.1. Model Spectrum

A group of machine learning algorithms will be chosen to develop a broad benchmark comparison, encompassing interpretable baselines in addition to high-accuracy ensemble and deep learning algorithms: Linear/Interpretable Baseline: Logistic Regression will be the baseline to test the predictiveness of a basic, linear model relationship. Tree-based ensemble techniques, i.e., Random Forest (RF) and Gradient Boosting Machines (GBM), e.g., XGBoost or LightGBM, will be employed. These models specialize in handling high-dimensional, mixed-type data and in capturing rich, non-linear interactions among features, which is critical in approximating the complexities of trade risk. A Multi-Layer Perceptron, or Artificial Neural Network (ANN), will be built in an effort to discover intricate, latent patterns of prediction that may elude tree-based approaches.

3.3.2. Hyperparameter Optimization and Validation

Data will be divided into training, validation, and one remaining unUsed hold-out test set (e.g., 70%/15%/15% split) to completely validate generalization performance. Training set cross- validation will be performed using K-fold cross-validation, and validation set will be utilized to fine-tune the hyperparameters of each model for example tree depth, learning rate, and regularization strength to tune performance and prevent overfitting.

3.3.3. Performance Evaluation

To measure performance, we will use specific metrics according to the financial risk business scenario.
Primary Metric: The Area Under the Receiver Operating Characteristic Curve (AUC-ROC) is the main metric to test our discrimination ability.
Business-Relevant Metrics: Here we will focus specifically on the 'Delayed' classes. Precision, Recall and F1-score will be calculated on a per-class basis. High recall in this class is essential to minimize losses from high-risk transactions.

3.4. Model Interpretability and Impact

By achieving our third objective, the research will take another step forward in achieving predictive accuracy. As a result, financial institutions can effectively apply the models to meet the need for clarity in decision-making and compliance. The central contribution of the framework is based on this interpretability phase:
We will use the SHapley Additive explanations (SHAP) method for both local and global interpretabilities. This will likely be a Gradient Boosting Machine (GBM) or Artificial Neural Network (ANN). The value of SHAP can be used to determine the contribution of three risk levels (country, bank and behavior) to the prediction. Additionally, SHAP can provide local interpretability, single transaction risk interpretation that can assist banks in the credit approval process.
Feature Effect Visualization (PDPs): Here we can create partial dependency plots (PDPs) to represent the marginal effects of predictor variables on expected settlement outcomes. This will be able to depict the expected non-linear relationships. In particular, with sharp differences in payment behavior risk outside a specific country-risk range. This sophisticated, multi-stage process can provide us with a robust and understandable framework for prediction that can strengthen risk management in export finance.

4. RESULTS AND DISCUSSION

4.1. Descriptive Characteristics and Distribution of the Target Variable

For this analysis, we took sample of N=18,945 records from approximately 130,000 transaction records processed over five years. The following results are based on the three broad settlement outcomes:

- On-time: 78.2% of transactions (N=14,814)
- Early: 15.5% of transactions (N=2,936)
- Delayed: 6.3% of transactions (N=1,195)

The prevalence of the 'On Time' class made it a requirement to highlight strong performance indicators such as Recall and F1-Score, especially for the high-risk "Delayed" class. These transactions have data from a total of 85 importing countries. Of these, the top five countries were present in 65% of the total bill. This highlights the significance of country-related risk.

4.2. Comparative Model Efficacy

This research also has the following objective: to develop and verify several machine learning algorithms. In so doing, we have tested 15% of the data with Logistic Regression as the baseline, and Random Forest, Gradient Boosting Machine, and Artificial Neural Network as other algorithms. The results can be seen in Table 1.

Table 1. Comparative Model Performance on Hold-out Test Set Multi-Class Classification

Model	Primary Metric (AUC-ROC Macro)	F1 Score (Macro-avg)	Recall (Delayed Class)	Precision (Delayed Class)
Logistic Regression (Baseline)	0.724	0.651	0.493	0.589
Random Forest (RF)	0.841	0.783	0.718	0.755
Artificial Neural Network (ANN)	0.882	0.825	0.791	0.788
Gradient Boosting Machine (GBM)	0.915	0.864	0.854	0.831

The findings clearly indicate that the Gradient Boosting Machine (GBM) model provided better prediction performance on all important metrics. The Primary Metric (AUC-ROC Macro) value of Gradient Boosting Machine (GBM) was found to be 0.915 compared to Logistic Regression model (AUC-ROC=0.724), which easily demonstrates more discriminatory predictive power between early, timely and delayed classes.

The GBM model performed strongly against the minority, high-cost-of-error 'Delayed' class. It had a Recall of 85.4%, that is, it identified more than four-fifths of the high-risk transactions correctly. This result powerfully supports the fundamental postulate of the AI-Driven Predictive Modeling Framework that high-powered algorithms can better capture complex, nonlinear relationships in high-dimensional financial information than low-powered linear econometric models. The high accuracy (83.1%) of the GBM model also illustrates its operational effectiveness in reducing the false positive rate for example incorrectly labeling a bill as being delayed when it is not.

4.3. Analysis of Predictive Factors and Feature Significance

The second objective was to identify and quantify the relative significance of the predictor variables segmented into the three theory pillars of risk. By applying the Global SHAP methodology on the most accurate GBM model, the features were ordered and segmented by conceptual category.

Table 2. Pillar Contribution to Predictive Power

Risk Pillar	Aggregate SHAP	Dominant Features within Pillar	Conceptual Validation
Importer Country Risk	26.7%	Currency Volatility Index, Political Stability Index, Trade Experience Score	Trade Risk Theory (Macro)
Importer's Bank Attributes	14.8%	Bank Reputation Score, Bank Size Proxy, Correspondent Network Density	Trade Risk Theory (Institutional)
Transaction/Exporter Variables	3.2%	Normalized Bill Amount, Exporter Tenure	Transactional Factors

The explanation is in line with the core significance of the Behavioral Risk Framework, Importer Payment Behavior-related variables acting as the dominant predictors, accounting for close to 55% of the total explanatory capability of the model. The 'Average Past Delay (Days)' and 'Delay Frequency (Last 12 Months)' were discovered to be the two most significant variables, together having the predictive ability of the entire Country Risk pillar.

The Importer Country Risk attributes were the second most significant factor (≈27%), being almost entirely explained by the identified Currency Volatility Index, thus affirming classical Trade Risk Theory's assertion that macroeconomic financial stability has a direct effect on payment reliability.

Probably the Importer's Bank Attribute has more statistical significance in statistical terms ≈15% but essentially it amounts to ester's macroeconomic stability, which is more than unlikely.

4.4. Model Interpretability: Non-Linear Effects and Cross-Level Interactions

Follow-up with PDPs and local SHAP dependency plots helped us achieve our final goal – to achieve the ultimate goal of Model Explainability. Over there Plots indicated us that we may have unusual but interesting non-linear inaction that is confirmed case for us to apply state-of-the-art AI models.

4.4.1. Non-Linearities in Payment Behavior

In the case of the PDP measurement of 'Average Past Delay (Days)', we see that there is a very non-linear dependency between it and the estimated probability of a future 'Delayed' state. The probability is comparatively constant for average delays of around 5 days. Beyond that threshold, the estimated risk increases very steeply, exhibiting sigmoidal behavior, with the marginal cost of the sixth day of delay being considerably higher than for the first. This finding indicates that trade finance institutions must concentrate their risk reduction efforts not on meaningless history fluctuations, but on counterparties whose average delay has crossed this critical behavioral tipping point, thereby validating the frontier application of the Behavioral Risk Framework in an AI setting.

4.4.2. Cross-Level Interaction Effect

One of the major results of applied risk management is the confirmed cross-level relationship between Importer Country Risk and Importer's Bank Attributes. The research verified that the adverse effect of low 'Bank Reputation Score' (a meso-level institutional characteristic) on timely settlement is strongly magnified in high 'Currency Volatility Index' countries (a macro-level national characteristic). Low Volatility Countries: For low volatility countries, the expected default risk of a poorly-rated bank was 5.1%. For high volatility nations, the expected default risk of the same poorly-rated bank was 18.9%. This interaction empirically validates the rationale of the multi-level approach indicated by the theoretical framework of the study.

It demonstrates that institutional weakness (tarnished bank reputation) is a lightweight concern in well-structured environments, but is a material, synergistic risk factor in the presence of macroeconomic instability to facilitate differential pricing and collateral requirements according to the recommendation by the AI model. The resultant explainability guarantees these sophisticated decisions to be transparent, thus engendering confidence for banks to aspire to meet standards of risk management and governance.

4.5. Discussion

The empirical findings in this research present significant theoretical and practical contributions to trade finance risk management. The study was able to build an extremely accurate, interpretable forecasting method of export bill settlement results by combining three critical, though so far separate, pillars of risk: Importer Payment Behavior, Importer Country Risk, and Importer's Bank Attributes. One explanation for the weaker importance of the Importer’s Bank Attribute in relative terms could be given by restricted findings in correspondent bank quality depending on correspondent banks, because few very trusted foreign banks with high transaction volume dominate transactions. In such a context, the bank-level predictors will of course tend to be less discriminant. Moreover, they are likely under-captured or not at the same level of detail as behavioral and macroeconomic variables, which can curtail their statistical relevance.

4.5.1. Empirical Validation of the AI-Driven Predictive Model

The first consequence of this result is that the demonstrably improved performance of the GBM model confirmed that AI-Driven Predictive Modeling Framework is, indeed, an indispensable option of addressing trade risk EWS in high-dimensional contexts. GBM model achieved a Macro-averaged AUC-ROC of 0.915 and a respectable Recall of 85.4% of the highrisk ‘Delayed’ class. This is incomparably better than the performance of the Logistic Regression baseline model, proving the fact that traditional linear econometrics is ill-suited for the task of describing the non-linear, complex relationships in today’s global trade data. The strength of the GBM model lies in the fact that it can replicate relationships and recognize intricate patterns in the 6.3% minority class (N=1,195 bills) which more linear models are likely to overlook, thus enhancing the financial sector's capacity for recognizing infrequent but expensive risk events.

4.5.2. Theoretical Analysis of Predictive Determinants

The significance of the feature, measured by the SHAP framework, provides new empirical evidence of the comparative contribution of the three theoretical pillars of risk, which closely relates to the literature review aspect of the study. Prevalence of Behavioral RiskThe behavior pillar was the top predictor, taking up 55.3% of the overall prediction ability of the model. This is a strong confirmation of the Behavioral Risk Framework, which explains that historical transactional patterns and institutional norms are good predictors of future on-time settlement, perhaps even better than stable financial ratios. The dominating significance of dynamic indicators such as 'Average Past Delay (Days)' and 'Delay Frequency (Last 12 Mo)' trumps the significance of macro-level indicators, implying a trading partner's fixed past is the most significant to influence future on-time payments. This shifts the focus of risk assessment from static assessment of financial health to dynamic evaluation of behavioral predictions.

The macro-level Importer Country Risk factor explained the second largest percentage (around 26.7% of predictive power), with the largest influence being from the 'Currency Volatility Index' and 'Political Stability Index'. This verifies the correctness of the basic Trade Risk Theory hypothesis that payment fulfillment is significantly determined by sovereign and macroeconomic considerations.

The discovery that this factor is secondary to behavioral experience by individuals implies that although nation risk establishes the outer limit of trade reliability, the importer's own behavior will decide the fact of outcome within the constraint. The most subtle, but significant, component was the Importer's Bank Attributes (approximately 14.8%).

This indicates that although intermediary banks enable bill settlement, their institutional stability is less of an overt measure of default than the importer's willingness or capability to pay, based on behavioral experience and national instability. This nuanced finding helps to inform the rationing of due diligence capacity by trade finance institutions.

4.5.3. Nonlinear Effects and Practical Applications

The model's interpretability delivered empirical justification for the use of non-linear modeling, and this produced practically valuable implications for terms of trade credit pre-shipment screening and negotiations. Critical Turning Point in Delays in Payment- Identification of a nonlinear inflection point in the 'Average Past Delay' is a critically significant practical outcome. The model indicated that it was only after the mean historical lag rose above about 5 days that 'Delayed' risk rose significantly. It is a highly significant finding for the 78.2% of transactions which lie in the 'On Time' category.

It indicates that risk management systems should not regard all historical lags equally. Instead, it should seek out those counterparties whose past history has lately crossed this threshold. This finding emphasizes the necessity of early implementing focused intervention. Inter Level Risk Synergy The primary discovery validating the multi-level theory model is the recognized synergistic cross-level association amongst Country Risk and Bank Attributes. Low rated bank's expected default risk turned out to be nearly four times greater in high Currency Volatility countries (18.9%) than in stable economies (5.1%). The empirical result fills squarely the research gap on contextual integration. It clearly illustrates that structural vulnerability of an intermediary bank is aggravated significantly under a macroeconomic environment that is unstable. To exchange financiers and policymakers, this implies that risk must be dynamically estimated; a mere 'safe country' label will not do, and a bank's reputation must largely depend on the volatility of its business environment. This discovery lends clarity to the work of sophisticated, differential trade credit price model development whereby the risk perception of an importer is influenced not merely by additive variables but the multiplicative combination of the bank profile and economic instability within the nation.

4.5.4. Bridging Conceptual and Methodological Contributions

This investigating is twofold: (i) conceptual, combining the models outlined in sections 2.1 and 3.1 along new components to contribute of modeling network properties; (ii) methodological presenting that advanced machine learning algorithm (GBM) with light interpretable auxiliaries ones can lead to greater prediction accuracy satisfying the requirement from financial regulators for transparency (BIS, 2014). The effective separation of the 'Delayed' group up to 85.4% Recall more (behavioral-based with 55.3% importance) provides a generalized and acceptable tool to enhance pre-shipment counterparty risk management by reducing liquidity and credit risk in volatile global supply chains.

5. CONCLUSION

In this study, an integrated AI driven predictive model for export bill settlement has been developed which was tested to be highly accurate and transparent by integrating the key concepts of BRF, Trade Risk Theory and AI-Driven Predictive Modelling Framework. The findings support the conclusion that typical linear risk assessment metrics are obsolete, and that complex ensemble learning mechanisms such as Gradient Boosting Machines must be leveraged to tackle the multi-layered, non-linear complexities of international trade finance. At a practical level, we present one potential complete design for trade finance institutions to enhance their counterparty risk assessment, ensure compliance with regulatory requirements and promote financial stability.

The overall finding is based on the empirical superiority of non-linear models and the significance of predictive features. The study determined that individual Payment Behavior is the most crucial forecaster of settlement outcomes, verifying that an importer's history of meeting obligations takes precedence over overall country or bank stability. The primary discovery of a robust non-linear inflection point in historical payment lateness shows that risk is not growing linearly, but instead becomes considerably greater after a behavioral threshold is reached. The analysis demonstrated the necessity for a multi-level approach by identifying significant cross-level risk synergy, in which risks within an importer's intermediary bank are drastically amplified when the bank is located in a nation with high macroeconomic volatility. The findings in general suggest that the management of trade risk necessitates a change from static generalized analyses to dynamic behavior-based AI-driven projections. Implementation and Regulation Recommendations On the basis of the above theory and empirical evidence, the following recommendations are made to improve risk management in export finance:

5.1. Prioritize Behavior-Driven Risk Monitoring

Banks must promptly reorient their credit models to prioritize dynamic behavioral characteristics over static institutional or financial information. Priority must be given to monitoring and identifying importers for which the rolling average or frequency of previous payment delays is close to the specified non-linear inflection point. This allows preemptive action, e.g., changing trade credit terms or demanding collateral, prior to the counterparty assuming a statistically riskier profile. SHAP-based explanation tools must be implemented at the transaction level in order to give underwriters a clear, acceptable reason for risk decisions, e.g., "Predicted delay owing to high historic delay frequency and heightened country risk exposure."

5.2. Carry out Dynamic, Synergistic Risk Valuation

Regulatory and financial institutions need to move away from additive risk assessments. Export credit pricing and provisioning need to capture the multiplicative interaction between the importer's bank stability and the importing country's macroeconomic volatility.

Counterparties based in countries with high currency or political risk need to be subjected to more stringent banking regulations, since the model demonstrated that institutional weakness and macroeconomic volatility entail a synergistic risk. This proposal endorses a more precise, risk-sensitive pricing framework that mirrors the actual exposure as found by the AI model in a direct way.

5.3. Implement Explainable Machine Learning for Regulatory Compliance

To foster the production deployment of such high-precision models, institutions must require the utilization of explainable AI (XAI) frameworks such as SHAP and Partial Dependence Plots. Lowopacity deep learning or ensemble models cannot be used to their full potential without humanreadable, transparent outputs in order to meet regulatory demands for openness and auditability of financial decision-making, as underscored by global regulatory scrutiny of AI in finance. Deployment of XAI guarantees predictive capability is transformed into actionable, auditable results in a manner consistent with current risk governance expectations.

5.4. Ongoing Model Validation

Based on the dynamics of international trade and the impact of geopolitical occurrences, the predictive model has to be considered a dynamic tool. Organizations have to adopt a policy of ongoing monitoring and recalibration of the model, i.e., assess the stability of feature importance rankings and the position of the behavioral inflection point. This keeps the forecast accuracy of the model high, conforming to changes in macroeconomic conditions or changing global payment norms.

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