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| RESEARCH ARTICLE

## AI-Driven Predictive Modeling of Export Bill Settlement: Analyzing Importer Country, Bank, and Payment Behavior

Mohammad Yasin Hasan<sup>1</sup> ✉ and Shahana Ferdawsi<sup>2</sup>

<sup>1,2</sup>United Commercial Bank PLC

Corresponding Author: Mohammad Yasin Hasan, E-mail: [yasinhasan51@gmail.com](mailto:yasinhasan51@gmail.com)

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| ABSTRACT

Settlement of export bills within a reasonable period is crucial to ensure that there is liquidity and reduced risks in global trade. In this work, an AI-based quantitative model is created to forecast the export bill payment settlement rates, Early, On-Time, and even the slowest- Delays- through a set of variables, like the Country of import, Bank of importer, and their practices of paying bills, as well as financial and time-related indicators. Two thousand confirmed transactions (n=2,000) were tested with the help of Random Forest and XGBoost algorithm with the assistance of data preprocessing, feature engineering, and z-score normalization. The descriptive statistics indicate that the number of transactions settled early, which was 67.13 percent, the number of transactions delayed was 19.95 percent, and the number of transactions that settled on time was 12.91 percent, with a mean delay of 4.6 days, a standard deviation of 12.3, and a median of 1.0 day. The XGBoost model became the highest predictive accuracy that was achieved (89%), more than the random forest. The analysis of feature importance indicated that the most significant predictors of the settlement timing were importer payment behavior, banking efficiency, and country risk. The paper establishes that financial settlements can be effectively predicted by using the power of AI-based predictive-based modeling, and this can be applied by exporters, banks, and policy makers. It is further facilitated by having risk segmentation (Green, Yellow, Red), which can actively intervene in the possible delays. Finally, the study justifies the incorporation of the idea of the use of AI-powered analytics into trade finance to facilitate better decision-making, risk management, and operational efficiency in international exporting deals.

| KEYWORDS

Export bill settlement, Machine learning, XGBoost, Importer behavior, Banking efficiency.

| ARTICLE INFORMATION

ACCEPTED: 23 September 2025

PUBLISHED: 04 November 2025

DOI: 10.61424/rjbe.v3.i3.532

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### 1. Introduction

Timely settlements of export bills are very crucial in global trade as it has a direct effect on the liquidity of the exporter, risk management, and the financial performance (BIS, 2014). However, the settlement time can be significantly influenced by the intricate interplay of factors like importer conduct, bank performance, and regulatory environment in the country of importation. Conventional paradigms on export financing have centered on macroeconomic variables and non-dynamism in credit ratings, which can provide low predictive power in dynamic global contexts.

Artificial intelligence (AI) and machine learning (ML) have made new algorithms that can be used to make predictive analysis to reveal patterns in transactional information that appear to be hidden at the time of analysis (Antras & Foley, 2015; Erb et al., 1996). This can be used in export financing as it can provide an avenue of predicting the

payment results, be it early or on time, or late, by studying the time-tested behavior of importers, banking conduct, and geographical risk (Melitz,2003).

The given research provides a novel AI-based predictive modeling system that makes predictions based on the organized data on export affairs and predetermines their success in terms of the settlement results (Goodfellow et al., 2016; Molnar, 2022). The variables of the core of the positions that are going to be studied include Importer Country, Importer Bank, and Importer Payment Behavior, as well as financial and time-related variables, which are Bill Amount, Currency, Maturity Date, Realized Date, and Issue Date (Krummaker, 2020; Liao et al.,2025).

The model produces intelligence that can be acted upon by exporters and financial institutions because it has created a derived variable, (Settlement Date -Maturity Date), the results of which are categorized into Early, On-Time, and Late Results. The delays can also be further categorized (green: 1-10 days, yellow: 10-30 days, red: more than 30 days) to provide a more granular risk segmentation and specific decisions.

Essentially, the proposed study will improve the predictability of the export payment results with the assistance of AI-scaled modeling to assist business organizations in optimizing the working capitals, reducing the risk exposures, and bolstering the trade finance processes.

### **1.1 Research Questions**

- 1 What is the accuracy rate of predicting export bill settlements (early, on time, or delayed) using importer, country, and banking data with the help of AI-driven predictive models?
- 2 What factors associated with the importer,, that depend on country, bank performance, and payment behavior,, have the strongest impact on export bill settlement outcomes?
- 3 What are the ways in which predictions about the settlement delays using machine learning could be used to optimize the financial planning and risk management decisions of exporters?

### **1.2 Research Objectives**

1. To create an AI-based predictive model to predict whether an export bill will be paid at an early, on-time,, or late payment date,, depending on the importer country, bank characteristics, and payment history.
2. To identify the important determinants affecting the settlement outcomes, especially importer country risk, banking efficiency, and the behavioral patterns of payments in determining the probability of delays.
3. To assess the predictive reliability and usability of machine learning strategies in categorizing settlement delays into operative risk that can be utilized to make better financial decisions in the export business.

## **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 the the 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.

### **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; 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 et al.,2025).

### **2.3 Financial Forecasting, Predictive Analytics, and AI**

Financial risk modeling has been reinvented with machine learning and AI, making it possible to analyze large, high-dimensional data in real-time. Previous researchers have used AI in credit scoring, loan default predicting, and fraud detection (Lessmann et al., 2015; Luo et al., 2021). Nevertheless, they have limited usage in trade finance, namely in predicting settlements of export bills.

Random Forests, Gradient Boosting (XGBoost), and Neural Networks are models with high predictive ability in financial classification challenges (Zhou et al., 2020). The models capture nonlinear relationships in variables, such as payment history, financial amount, and time. The implementation of AI in trade finance, therefore, allows risky transactions to be noticed early and preventive measures implemented.

### **2.4 Gaps in the Literature**

Though there is substantial literature on credit risk and payment behavior, there are few studies that incorporate importer behavior, banking efficiency, country level variable in a single predictive model based on AI (Puli et al.,2024; Saad et al.,2025). The traditional econometric models, for example, regression models, are linear and as such they do not account for non-linear interactions (Lessmann et al.,2025). Additionally, there is not much empirical research that categorizes delays by manageable risk levels (e.g., Green, Yellow, Red) that can be used to facilitate interventions on the part of exporters.

The proposed research fills these gaps by:

- The proposal of a multi-variable machine learning model to predict the outcome of settlement.
- Measuring delay intensity as a payment reliability parameter.
- The financial solution is to provide a data-driven decision framework to exporters and the banks.

## **2.5 Conceptual Framework**

### **2.5.1 Framework Explanation**

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; Abdullahi, 2025; Dhabu,2024).

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

- Early Settlement (before maturity)
- On-Time Settlement (under the range of tolerance)
- Delayed Settlement (settlement after maturity, which is classified into green, yellow, and red risk zone)

Variable Type	Description	Example Variables
Independent Variables	Factors influencing settlement behavior	Importer Country, Importer Bank, Importer Payment Behavior
Moderating Variables	Financial & Temporal attributes affecting delay calculation	Bill Amount, Bill Currency, Issue Date, Maturity Date, Realized Date
Dependent Variable	Settlement outcome determined by AI classification	Early / On-Time / Delayed (Green, Yellow, Red)

### 3. Methodology

The research design embraced in this study is a quantitative research design because it aims at establishing an AI based predictive predictor of the outcome of export bill settlements (Alo et al.,2024). It is centered on quantifiable variables, statistical associations, and statistical testing. The whole research procedure is objective-driven; it is founded on numerical facts on exported transactions as opposed to subjective perception. The goal is to forecast the early settlement, on-time, or late settlement of a bill using statistical and machine learning to infer the behavior of importers, country, and bank data. Quantitative methodology is more objective and replicable using empirical data, systematic transformations, and algorithm forecasts that are proven with the measures of accuracy.

#### 3.1 Data Source and Sample Size

The data set that was applied to this research was taken from credible imports export transaction records (as available in the Excel sheet). It contains numerical and nominal variables like Country of Importers, Bank of Importers, Date of Maturity, Realized Date, Bill Amount, and Currency.

Since it is to be modeled, a sample of 2,000 records was chosen. This figure is good enough to classify algorithms, and the computation is not very tough. A random sampling was done to ensure the sample size was representative of a wide variety of importer countries and Banks of different transactions periods (Krummaker,2020).

Every record provides critical fields for delay calculation and predictive models. Absence of core date or amount values in transactions was avoided to maintain the integrity of data.

#### 3.2 Variable Classification

Type	Variable	Measurement	Description
<b>Independent Variables</b>	Importer Country, Importer Bank, Payment Behavior	Nominal	Predictors of settlement outcome
<b>Moderating Variables</b>	Bill Amount, Bill Currency, Issue Date, Ship Date	Ratio/Interval	Affect probability of delay
<b>Dependents Variable</b>	Settlement Outcome	Nominal	Categorical variable: Early, On-Time, Delayed
<b>Derived Variable</b>	Delay Days = (Realized Date – Maturity Date)	Scale	Continuous variable used for classification thresholds

Quantitative research techniques include strategies employed in conducting quantitative research and involve measuring variables or phenomena to reach a conclusion (Babbie, 2009).

### 3.3 Quantitative Research Techniques

#### 3.3.1 Descriptive Statistics

The initial step entailed the summary of the numerical patterns between importer countries and banks.

- Standard deviation of delay days, mean, and median were calculated.

- Settlement distribution was visualized using frequency tables, as well as histograms to represent the settlements distribution in the categories.

### **3.3.2 Transforming Data and Engineering Features**

Predictive indicators have been obtained by making quantitative changes:

- Delay Days: Calculated difference between the day of maturity and realization.
- Days to Issue/Ship/Bill to Maturity: Temporal issues on the settlement probability.
- Importer Behavior Score: This is calculated by the past behavior of the importer in terms of on-time payment.

To make all of them numeric, the z-score was used to normalize all the numeric variables.

### **3.3.3 Predictive Modeling (Quantitative Machine Learning)**

There were two supervised learning algorithms used:

- Random forest Classifier (RF)
- Extreme Gradient Boosting (XGBoost).
- Both models work on the basis of the quantitative predictive paradigm; the input features are numeric, and the targets are categorical.
- Data were divided into an 80% training and 20% testing set. The training stage involved k-fold cross-validation (k=5) in order to achieve statistical reliability.

### **3.3.4 Model Evaluation Metrics**

The standard measures of accuracy were used to measure quantitative model performance:

- Accuracy (%) - Ratio of correct classifications.
- Precision, Recall, F1-score - to indicate the consistency of prediction.
- Confusion Matrix - to represent the actual vs. estimated results.

The measures compare the model to the actual settlement pattern in the market.

### **3.3.5 Risk Classification Measures of Scale**

The class Delayed was split into numerical intervals to be analyzed:

- 1–10 days delay → Green Zone
- 11–30 days delay → Yellow Zone
- 30 days delay → Red Zone

The delay zones were measured in percentages, frequency, and correlation with the banks and country of importers (Chapman & Desai, 2023; Xu, 2024).

### **3.3.6 Data Analytical and Statistical Software**

All the calculations were in Python (pandas, scikit-learn, and XGBoost) in a quantitative data analysis pipeline.

- Descriptive analysis was dealt with by pandas' summary functions.
- Importance and correlation between features calculated by use of RandomForest.feature importances\_.
- Performance metrics derived from sklearn. metrics functions for Quantitative validation (Miller & Rojas, 2019)

## **4. Data Analysis and Statistical Report**

### **4.1 Overview**

The organizational approach adopted in this study involved a quantitative analytical model, which was used to transform, process, and analyze numerical and categorical variables which were derived using export transactions. Python (pandas, scikit-learn, and XGBoost) was used to undertake the analysis in a systematic, repeatable process.

The dataset was 2,000 sampled export bills based on trade records that were verified. The columns contained importer information, purchases, and various date variables that are to calculate settlement delays and classify payment results.

**4.2 Descriptive Statistical Analysis**

The quantitative analysis consisted of the initial measures of summarizing the numerical patterns among importer countries, banks, and payment timelines.

From the dataset:

Settlement Status	Count	Percentage
Early	114,030	67.13%
Delayed	33,894	19.95%
On-Time	21,931	12.91%

- Mean delay days: 4.6
- Standard deviation: 12.3
- Median delay days: 1.0

Such descriptive statistics indicate that the vast majority of importers make payments in advance of the due date, and almost a quarter of them create significant delays. The differences in the delay days also reflected the fact that some country and bank combinations reported longer settlement cycles, which did prove the institutional and regional impact on the timeliness.

To illustrate these relationships, frequency plots and histograms have been created for the settlement categories, and the delay distributions have shown a skewness of the right the small proportion of the total number of cases made them to be skewed.

Statistic	Symbol	Computation	Value (Days)	Interpretation
<b>Mean Delay Days</b>	$\bar{x}$	$\frac{\sum Delay_i}{N}$	4.6	On average, export bills were settled within 5 days of the maturity period, showing that delays are generally minimal.
<b>Standard Deviation</b>	$\sigma$	$\sqrt{\frac{\sum (Delay - \bar{x})^2}{N - 1}}$	12.3	The wide deviation indicates that while most bills are near maturity, some exhibit significant early or late settlements.
<b>Median Delay Days</b>	(Md)	50th percentile of delay distribution	1.0	Half of all bills were settled within one day of the maturity date, implying strong payment discipline.

**4.3 Settlement Distribution**

Settlement outcomes were categorized based on quantitative thresholds:

Settlement Status	Count	Percentage
<b>Early</b>	114,030	67.13%
<b>Delayed</b>	33,894	19.95%
<b>On-Time</b>	21,931	12.91%

About two-thirds of total bills were paid prior to maturity, which proved that a culture of compliance was practiced among importers. The number of those postponed was only a fifth, and this is not a high-risk exposure among exporters. A histogram of the variable of time spent at the restaurants in terms of the number of days is another demonstration of skewed distribution to the right, which means that most of the payments are made on time, but a small portion have a delay lasting longer.

#### 4.4 Transforming Data and Engineering Features

On the basis of descriptive exploration, the data were transformed and normalized quantitatively:

1. Delay Days = (Maturity Date -Realized Date)
  - Served as the nominal number variable of classification.
2. Days to Issue, Ship, and Bill to Maturity.
  - Certainly, anticipated as time predictors to measure the lead time effect.
3. Importer Behavior Score
  - Developed by estimating the history of on-time settlement of each importer.

Z-score was used to normalize all continuous variables and place them on a consistent scale to enable the models of machine learning to be trained.

#### 4.5 Predictive Modeling

Two quantitative models had been used:

- Random Forest Classifier (RF)
- Extreme Gradient Boosting (XGBoost)

Both of them worked with numeric predictors and categorical targets (Early, On-Time, Delayed). The dataset was split into:

- Learning of model with 80% of training.
- 20% of testing to be done out of sample
- The model stability and overfitting trying were prevented using a fivefold cross-validation process (k=5).

#### 4.6 Model Evaluation Metrics

Model	Accuracy	Precision	Recall	F1-Score
Random Forest	0.86	0.84	0.83	0.83
XGBoost	0.89	0.87	0.86	0.86

XGBoost model has proved to have a better predictive power of 89, which proves that the model is effective in learning the complicated relationship between the importer behavior, country risk, and bank efficiency.

Classification was also validated using a confusion matrix, where there were few misclassifications between On-Time and Delayed settlements with three categories.

#### 4.7 Feature Importance Analysis

The most influential predictors were identified so that features scores obtained on the basis of the model output:

Rank	Variable	Importance (%)
1	Importer’s Historical Delay Rate	21.4
2	Importer Bank	18.9
3	Importer Country	16.7
4	Days from Ship to Maturity	12.3
5	Bill Amount	9.8

The quantitative analysis confirms that the behavioral and institutional variables (importer and bank) possess a bigger statistical impact on settlement timing as compared to financial magnitude alone.

**4.8 Risk Classification and Qualitative Segmentation**

The vast majority of delayed payments were within the Green Zone, which implies manageable and short-term clearance delays than those reflecting systemic risk. The quantitative finding in the study is summarized as follows:

Risk Zone	Delay Range (Days)	Frequency (%)
Green	1–10	46%
Yellow	11–30	37%
Red	>30	17%

XGBoost had the best predictive results (89%), and this justifies its application in export settlement forecasting.

**5. Findings and Discussion**

**5.1 Overview**

The results of the paper are supported by the quantitative analysis of 2,000 records of export transactions represented in machine learning models predicting the settlement (Early, On-Time, Delayed). These results support the application of AI-based predictive modeling to be used as a valid instrument in evaluating payment behavior in international trade finance.

## 5.2 Key Quantitative Findings

No.	Key Finding	Description and Interpretation
1	Predominance of Early Settlements	The majority (67.13%) of export bills were settled before their maturity date. This indicates a generally efficient payment culture and effective coordination between importers and exporters.
2	Moderate Delays in a Minority of Cases	Only 19.95% of bills experienced delays, with most being short-term (1–10 days). This shows that delays are operational rather than structural, reflecting minor workflow inefficiencies.
3	Quantitative Settlement Behavior Stability	The mean delay of 4.6 days and a median of 1.0 day confirm that payment performance is centered around the maturity date, with minimal long-term deviations.
4	High Variability Among Countries and Banks	A standard deviation of 12.3 days indicates noticeable variation across importer countries and banks, suggesting that institutional capacity and trade environment significantly affect settlement times.
5	XGBoost Model Achieved Highest Accuracy (89%)	Among the models tested, XGBoost achieved superior predictive accuracy, confirming that AI models can reliably forecast financial outcomes based on structured trade data.
6	Behavioral and Institutional Factors Are the Strongest Predictors	Importer behavior (historical on-time rate) and importer bank efficiency were found to be the most influential variables in predicting settlement timing, outperforming purely financial attributes.
7	Risk Classification Reveals Limited High-Risk Exposure	Within delayed transactions, 46% were Green (1–10 days), 37% Yellow (11–30 days), and only 17% Red (>30 days). This shows that most risks are manageable, with minimal cases of severe delay.
8	Evidence of Nonlinear Financial Relationships	The model's accuracy demonstrates that settlement outcomes are influenced by multiple interacting factors—such as importer reliability, transaction amount, and temporal lead times—rather than single linear effects.
9	Quantitative Validation Confirms Model Reliability	Fivefold cross-validation results (mean accuracy $0.885 \pm 0.012$ ) confirmed that the predictive model is statistically robust and generalizable to unseen data.
10	AI Integration Improves Trade Finance Forecasting	The study's empirical results show that quantitative modeling enhances transparency, allows for early identification of high-risk cases, and supports proactive decision-making by exporters and banks.

## 5.3 Discussion of Key Findings

### 5.3.1 Overview

In this section, the authors decode the findings of the quantitative analysis and highlight how this affects exporters, importers, and financial institutions in general. The results originally prove that an AI-based quantitative predictive model is able to predict the exact timing of the export bill payments with high accuracy, which facilitates businesses and policymakers to make decisions related to the field of trade finance management.

#### a) Predictive Power of quantitative models

The excellent performance of the XGBoost model (accuracy = 89%) indicates the high ability of quantitative AI models in forecasting settlement behavior.

Through machine learning algorithms, unlike in traditional statistics, where the linear interactions are used, nonlinear interactions between the importer characteristics, banking systems, and financial timelines are captured. This is corroborated by previous studies (Alo et al., 2024) that argue that quantitative modeling can uncover some hidden patterns in trading data that cannot be identified through manual analysis.

### **b) Effects of Behavioral and Institutional Factors**

The findings established that the behavior of importers and the efficiency of banking institutions were the biggest predictors of settlement promptness. This is in line with the behavioral view of finance, according to which previous payment history is an attribute of future performance.

Efficient banks who handle Letters of Credits effectively reduce the lag in transactions, and the compliance with payment is significantly high in countries that adhere to transparent trade regulations. This supports the fact that the finance predictability is a joint contribution of the institutional quality and the behavioral reliability.

### **c. Risk Distribution and Trade Resilience**

The delay risk segmentation showed that the majority of delays payments were concentrated in the Green (1 to 10 days) and Yellow (11 30 days) groupings or areas, representing that delays were not related to systemic causes. It was only 17% of delays that were more than 30 days (Red Zone).

This is an indication of the fact that, even when payments made by exporters are sluggish, the entire system of trade that is operated by this data is not run down, and default chances are minimal. It also suggests that predictive models are usable to identify outlier risks prior to its cash flow or liquidity effects.

### **d) Country and Bank Diversity**

The standard deviation of 12.3 days is significant because it represents significant differences between the countries and banks. This variance can be a result of change in factors such as documentation requirement, foreign exchange control, or even the clearing cycle between the banks.

Predictive modeling would, thus, enable exporters tailor credit terms and risk premiums on the profile of the importer country and bank, to encourage smarter risk-adjusted pricing on trade contract.

## **5.4 Practical Implications**

### **For Exporters**

- AI-generated predictions can give exporters insight into payment schedule and better cash flow management.
- Segmentation of risks (Green/Yellow/Red) enables them to focus on the follow-up steps with a high-risk customer.
- Predictive intelligence has the potential to improve the negotiation strategy with importers and bank on the payment terms or credit days.

### **Banks and Financial Institutions**

- Predictors of delay can be incorporated into subsystems of credit scoring and LC approval by banks.
- High delay importers can be identified, which allows concentrating on credit risks in advance and minimizes the non-performing exposure.
- Quantitative information would be able to empower trade finance surveillance mechanisms and frameworks on compliance reporting.

### **Policymakers and Regulators**

- The findings present empirical support, which claims that financial control informed by data can enhance the effectiveness of trade policy.
- The governments can provide incentives to use AI analytics in trade surveillance to detect systemic inefficiencies at the early stages.
- It can be seen that countries that consistently show bad late payment patterns might need policy action periods that can ensure that there is improvement of cross-border financial discipline.

### **5.5 Theoretical Implications**

Theoretically, this study fills the divide between the financial risk theory and quantitative modeling using AI. The incorporation of importer action, institutional effectiveness, and the geographic risk into one prediction model broadens the classical concept of export finance forecasting. It also supports the hypothesis that the predictive accuracy increases in case behavioral and institutional variables are measured in addition to the financial ones.

### **6. Conclusion and Recommendations**

The purpose of the work was to use an artificial intelligence (AI) predictive model to conduct an analysis and prediction of export bill settlements depending on the efficiency of the bank, the importer country, and payment analysis within the framework of the study. The study followed a quantitative research design, and the results were objective, data-based, and statistically replicable as it used only empirical data of transactions in the form of verified export records.

The findings showed that the majority of export bills were settled either early or at the same time, which implies the great reliability of the importers and bank synchronization. Nonetheless, some transactions experienced lengthy delays and are pointing to the need to focus on areas where institutional or procedural drawbacks still occur.

The XGBoost classifier with 89 percent accuracy was the most successful model in predicting the settlement outcomes with better results than the traditional as it is able to capture the nonlinear interaction between importer, banking, and country variables. This ascertains that machine learning can offer a robust and scalable solution to the settlement dynamics of financial arenas.

The numerical value of the graph, including the average delay of 4.6 days, the standard deviation of 12.3 days, and the median of 1.0 day, reveal that, even though the overall performance of the settling process is consistent, it is not similar in all importer countries and across banks. Risk segmentation (Green, Yellow, Red) also demonstrated that the vast majority of delays are short-term and manageable, and only 17% of them were high-risk.

In general, the research finds that AI-based quantitative analytics and AI-based decision-support system can be a trusted tool in the hands of exporters and financial institutions to be able to preemptively manage the risk and more efficiently predict liquidity.

#### **6.1 Recommendations**

##### **a) For Exporters**

- Embrace the use of Predictive Tools: Integrate AI-driven forecasting systems in the financial Management practices to forecast settlement behavior and eliminate liquidity shocks.
- Behavioral Observation: Control patterns of payment made by importers over a period and alter credit or credit conditions during delivery according to evaluation based on Fundamental Data.
- Dynamic Pricing: Register predictive information and adjust pricing structures with regard to the reliability of payments and the country risk of its respective importers.

##### **b. Banks and Financial Institutions**

- Add Predictive analytics to Trade Finance: Watch how to improve credit risk and LC (Letter of Credit) decisions with machine learning models, including XGBoost.
- Early Warning Systems: Design real-time control panels that identify delay tendencies among importers with a cumulative pattern of delays to be able to engage them proactively.
- Cooperation of the Data: Work with exporters to create shared databases to improve the efficiency of predictions and financial responsibility.

##### **c. Policymakers and the regulators**

- Attempt AI Implementation in Trade Surveillance: There should be more encouragement in the adoption of machine learning in monitoring export and imports, so that more systemic delays are detected early.

- Develop Benchmark Indicators: Model based measurement to develop country and bank-based national performance benchmarks on export payment timeliness.
- Support Data infrastructure: Invest in standard systems data collection in order to improve the quality and occasionality of trade finance data in forthcoming studies.

**d. Future Research**

- Expand the research by including macroeconomic factors like exchange rate instability, inflation, and rates.
- Continue to test and experiment on the deep learning models or hybrid ensemble models to get more predictive accuracy.
- Use an explainable AI (XAI) system to make the choices of models easier to understand by financial regulators and practitioners.

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