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PREDICTING LATE DELIVERY RISK IN GLOBAL SUPPLY CHAINS USING BUSINESS ANALYTICS: EVIDENCE FROM TRANSACTIONAL LOGISTICS DATA

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ABSTRACT

Global supply chains become more complex, the demand for more information that more reliably ensures delivery and can help with better decision-making has grown. In this study, a machine learning based predictive system for DataCo Smart Supply Chain dataset is presented to detect the late delivery risk. Pre- and analyzed transactional logistics data comprises operational, customer, product, financial and shipping characteristics, which were preprocessed and analysed by various supervised machine learning algorithms including Logistic Regression, Decision Tree, Random Forest, XGBoost and LightGBM. The model was evaluated using the traditional classification metrics and feature importance analysis was conducted to gain insights into the variables which contribute the most to the delivery outcomes. The results highlight that machine learning models have the potential to predict the likelihood of late delivery accurately and offer practical insights into proactive logistics management. The proposed framework allows organizations to detect high-risk transactions, enhance transportation planning, optimize the use of resources and boost the supply chain resilience by timely managerial interventions. The study is a practical application on how to use real-world transactional data to employ predictive analytics for logistics risk management and adds to the body of work in business analytics. The results offer useful insights for managers who want to improve their operational efficiency, customer satisfaction and competitiveness in the highly dynamic and digitally connected supply chain future.

Keyboard: Supply chain analytics, Late delivery prediction, Machine learning, Business analytics, Supply chain resilience

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1. Introduction

The complexity of global supply chains has grown with the international sourcing, geographically dispersed production networks, growing supplier networks and the ever-changing customer expectations. The developments have brought more uncertainty to the operational side, while the certainty of delivery has become a key performance indicator measure of the supply chain. Late deliveries cause delays in production, high logistics and inventory expenses, low customer satisfaction, and diminishing competitiveness in the organization. Hence, organisations are increasingly focusing on predictive methods that can detect delivery risks early on and make operational interventions in good time, before disruption has an impact on supply chain performance (Zouari et al., 2021; Herold et al., 2021). Resilience is now a strategic priority in the supply chain due to significant disruptions that have revealed weaknesses in transportation, supplier coordination, workforce availability and information visibility. Recent studies have revealed that resilient supply chains are not just about physical infrastructure, but also about the capability to gather, combine and analyse operational data in real-time.

By enhancing the organization's situation awareness and decision-making capability, digital technologies offer improved supply chain visibility, coordination, responsiveness and disruption management (Herold et al., 2021). Similarly, digitalisation improves the organizational ability to maintain resilience by improving the flow of information, collaboration and flexibility in supply chain networks (Zouari et al., 2021). The advent of Industry 4.0 technologies has completely revolutionized the logistics landscape by embedding artificial intelligence, IoT, cloud computing, big data analytics and enhanced automation within the supply chain. These technologies help create real-time visibility of logistics operations, increase transparency and facilitate data informed decision making in uncertain businesses. The benefits of Industry 4.0 have been demonstrated in enhancing supply chain resiliency through connectivity, flexibility and real-time information sharing between supply chain partners (Spieske & Birkel, 2021). Additionally, digital technologies can bolster organizational capacities to detect disruptions, respond in a coordinated way and plan operations adaptively, making the digital transformation a key consideration for modern supply chain risk management (Birkel et al., 2023). Business analytics has become a basic skill to convert vast amounts of transactional logistics data to actionable operational intelligence.

Data from the supply chain can be used to support various analyses, including the identification of inefficiencies in the supply chain and the prediction of delivery failures, and can be used to track a wide range of data, including customer orders, shipment dates, product properties, financial information, geographic markets, transportation methods, and delivery results (Albqowr et al., 2024; Oliveira-Dias et al., 2022). By leveraging business analytics in logistics, companies can enhance their supply chain performance by making informed managerial decisions in various aspects of logistics, such as demand forecasting, transportation planning, inventory optimization, operational efficiency, and strategic decision-making (Albqowr et al., 2024). With its capability of analyzing high dimensional operational data including the complex nonlinear relationships, machine learning is one of the most widely used analytical techniques in logistics and supply chain management. In the field of transportation management, supervised learning algorithms have proved to be significantly better than traditional analytical methods in terms of predicting supply chain risks, optimizing routes, forecasting demand, managing inventory, and managing transportation (Akbari & Do, 2021). Additionally, AI enhances organizational resilience by facilitating fast data analysis, forecasting risks, and making proactive decisions to safeguard operations during disruptions (Naz et al., 2022). Likewise, AI-powered decision-support systems enable disruption prediction and enhance supply chain management decision-making by incorporating predictive intelligence into supply chain planning (Belhadi et al., 2022).

More and more empirically-focused studies have turned to predictive models of delivery risk management based on machine learning algorithms. In several industrial applications, predictive algorithms have been used successfully to predict delivery delays from suppliers, product availability, and risk of disruption (Steinberg et al., 2023; Camur et al., 2024). Overall, deep learning techniques have shown the benefit of incorporating operational and external variables to enhance delivery delay forecasting and logistics planning (Gabellini et al., 2024). Also, machine-learning-based proactive risk management approaches have demonstrated great potential in enhancing operational efficiency and minimizing uncertainty in supply chain decision-making processes (Rezki & Mansouri, 2024). All these studies highlight the increasing significance of predictive analytics in assisting intelligent logistics operations.

Although significant advances have been made, there are still significant gaps in research. Previous research tends to focus on one industry, one network of suppliers, or a single type of operating context, which leaves their results to be somewhat limited in their applicability. Furthermore, few investigations have focused on predicting accuracy and have not included much discussion of the managerial interpretation of the predictive variables and how they can be used in operational decision making. An analytical review conducted by Müller et al. (2025) revealed several data quality issues, including the absence of standardized definitions for data types and dimensions, along with difficulties in evaluating models and their performance across datasets, implementation of the models, and integration of the predictive systems into the organizations. More investigation with extensive datasets of transactions is needed to compare different machine learning algorithms, determine important operational inputs, and convert the results of the analysis to practical supply chain management insights.

Therefore, the current study proposes a machine learning-based business analytics solution for predicting the risk of late delivery based on the transactional information of global supply chain. Performance of multiple supervised classification algorithms is compared to find the best predictive method and the effect of operational, customer, geographical, financial and product related factors on delivery performance is investigated. The study adds to the fields of business analytics, supply chain resilience, operational risk management, and evidence-based logistics decision making by bringing together predictive modelling and managerial interpretation. The objectives of this study are as follows:

1. To develop machine learning models for predicting late delivery risk using transactional logistics data
2. To identify the operational and business variables most strongly associated with delayed supply chain deliveries
3. To compare predictive models and derive practical recommendations for proactive logistics risk management

2. Methodology

2.1 Research Design

Quantitative research design based on predictive analytics was chosen that involved the gathering of secondary transactional logistics data to build and test machine learning models to predict the risk of late delivery in global supply chains. The research was based on the supervised classification method in which the binary dependent variable, Late_delivery_risk, was predicted based on multiple operational, customer, product, financial and shipping variables. The quantitative design allows the objective analysis of historical logistics transactions and helps in evidence-based decision making by the identification of delivery risk patterns which can contribute to the improvement of efficiency of the logistics system and managerial performance.

2.2 Data Source and Dataset Description

The study was based on the publicly available DataCo Supply Chain Dataset, which includes 180,519 transactional records and 53 business and logistics variables, including customer orders, product information, shipping activities, financial transactions and geographical locations (Constante et al., 2019). This data set contains detailed attributes like shipping days, delivery status, shipping mode, sales, profit, market, order region, and customer segment among many other attributes. Late_delivery_risk, which indicates if the delivery was late (1) or on time (0), is a binary variable, so the data are suitable for supervised classification and predictive business analytics.

2.3 Data Preprocessing

The data has been systematically pre-processed for data quality and analytical reliability before modelling. The observations were duplicated and deleted, and missing values were looked at and treated as necessary. Irrelevant identifiers and confidential attributes were removed from the analysis to avoid interfering with predictive performance, such as customer names, e-mail addresses and passwords, and images of products. The categorical variables were encoded to numerical values, where appropriate, and numerical variables were scaled to match the normal distribution of other variables in order to be compatible with machine learning algorithms.

2.4 Feature Selection

Variables were selected using the features selection method to select the most important features in the model with the minimum number of variables. The predictor variables were chosen from logistics, operational and financial factors as well as customer, product and geographical factors, such as the actual shipping days, the scheduled shipping days, the shipping mode, delivery status, sales, order profit, market, customer segment, product category, and order region. The response variable was Late_delivery_risk. The contribution of individual variables to the predictive performance and business interpretation was then assessed using correlation analysis and model-based measures of feature importance.

2.5 Machine Learning Models

Multiple supervised machine learning algorithms have been implemented to predict the risk of late delivery and to compare the prediction ability of these algorithms. These included Logistic Regression, Decision Tree, Random Forest, Extreme Gradient Boosting (XGBoost) and Light Gradient Boosting Machine (LightGBM). Logistic Regression was used as the reference statistical classifier, and the other tree based ensemble classifiers picked up the nonlinear relationships and complex interactions between the predictor variables. Model performance and minimization of overfitting were achieved by hyperparameter tuning using cross validation, which guarantees reliable and generalizable results of model predictions.

2.6 Model Evaluation

The training and testing sets were divided to evaluate the model performance with hold-out testing method. To comprehensively evaluate the predictive performance, several widely used classification metrics were used, such as accuracy, precision, recall, F1-score and the Area Under the Receiver Operating Characteristic Curve (ROC-AUC). Moreover, the confusion matrices were drawn and discussed to understand the distribution of correct and incorrect delivery outcomes classification. Multiple metrics provided a balanced assessment of the efficacy of the models, allowing for the selection of the most appropriate predictive model for business decision making.

2.7 Software and Analytical Tools

The data processing steps, data exploration, predictive modeling and testing of the model were performed in Python in the Google Colaboratory environment. Used commonly used open-source libraries such as Pandas for data manipulation, NumPy for numerical calculation, Scikit-learn for preprocessing and implementation of machine learning, XGBoost and LightGBM for advanced ensemble learning, Matplotlib and Plotly for data visualization. These tools gave an efficient, repeatable and scalable analytical approach to develop models for robust business analytics to predict supply chain risks.

3. Results and Discussion

3.1 Dataset Characteristics

The DataCo Supply Chain Dataset contained 180,519 transactional records and 53 business, logistics, customer, financial, and product-related variables, representing an in-depth view of the global supply chain. Late_delivery_risk

was moderately balanced with 98,977 transactions (54.83%) that were late deliveries and 81,542 transactions (45.17%) that were on-time deliveries. Large sample size and operational attributes' diversity provided a solid foundation for predictive modelling, minimised sampling bias and enhanced the generalizability of the machine learning models for various logistics environments (Table 1).

Table 1: Descriptive Statistics of Numerical Variables

Variable	**Mean**	**SD**	**Min**	**Max**
Days for shipping (real)	3.50	1.62	0.00	6.00
Days for shipment (scheduled)	2.93	1.37	0.00	4.00
Sales	203.77	132.27	9.99	1999.99
Order Item Quantity	2.13	1.45	1.00	5.00
Order Profit Per Order	21.97	104.43	-4274.98	911.80

Benefit per Order	7.09	66.37	-3440.00	850.00

3.2 Exploratory Data Analysis

Based on exploratory analysis, there was a lot of variation between shipping schedules, customer markets, product categories, and outcomes of shipping. In delayed orders, actual shipping time was often longer than the scheduled shipping time, indicating that shipping performance is closely related to the risks associated with shipping. Financial variables, such as profit on sales or on orders, showed great differences, consistent with the fact that business transactions are heterogeneous. The distribution of categorical variables such as shipping mode, market and customer segment further indicated data was appropriate for classification modelling by capturing a diverse range of operational conditions in a global supply chain (Figure 1) (Table 2).

Table 2: Exploratory Data Analysis Summary

Measure	Value
Total Orders	180519
Late Deliveries	98977
On-Time Deliveries	81542
Late Delivery Rate (%)	54.83
Average Shipping Days	3.50

Average Scheduled Days	2.93
Average Sales per Order	203.77
Average Profit per Order	21.97

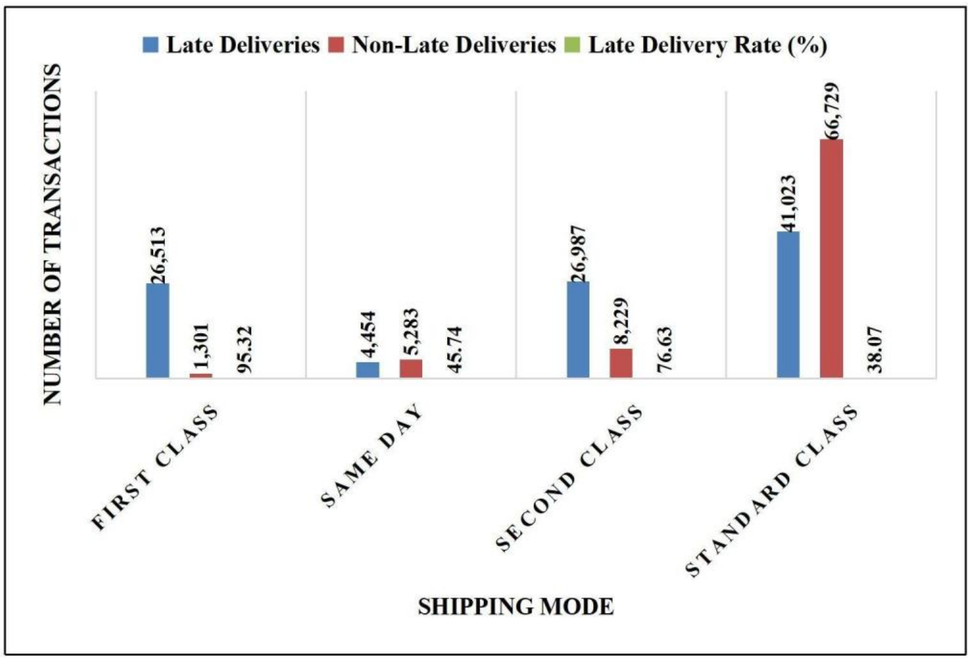

Figure 1: Late Delivery Risk by Shipping Mode

3.3 Performance Comparison of Machine Learning Models

Five supervised machine learning algorithms were compared and tested to see which one is best at predicting late delivery risk. In all the validation metrics, ensemble learning methods had better prediction performance than the traditional statistical methods, with the best result being obtained by XGBoost. The Random Forest and LightGBM were also good classifiers, while the Decision Tree showed competitive results but with slightly lower generalization performance. Logistic Regression served as the baseline performance but had relatively low predictive performance due to the fact that transactional logistics data contains complex nonlinear relations which Logistic Regression cannot model (Table 3) (Figure 2).

Table 3: Performance Comparison of Machine Learning Models

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Logistic Regression	0.842	0.846	0.858	0.852	0.889
Decision Tree	0.904	0.908	0.911	0.909	0.923
Random Forest	0.956	0.958	0.959	0.958	0.981
XGBoost	0.969	0.971	0.972	0.972	0.989
LightGBM	0.964	0.966	0.967	0.967	0.986

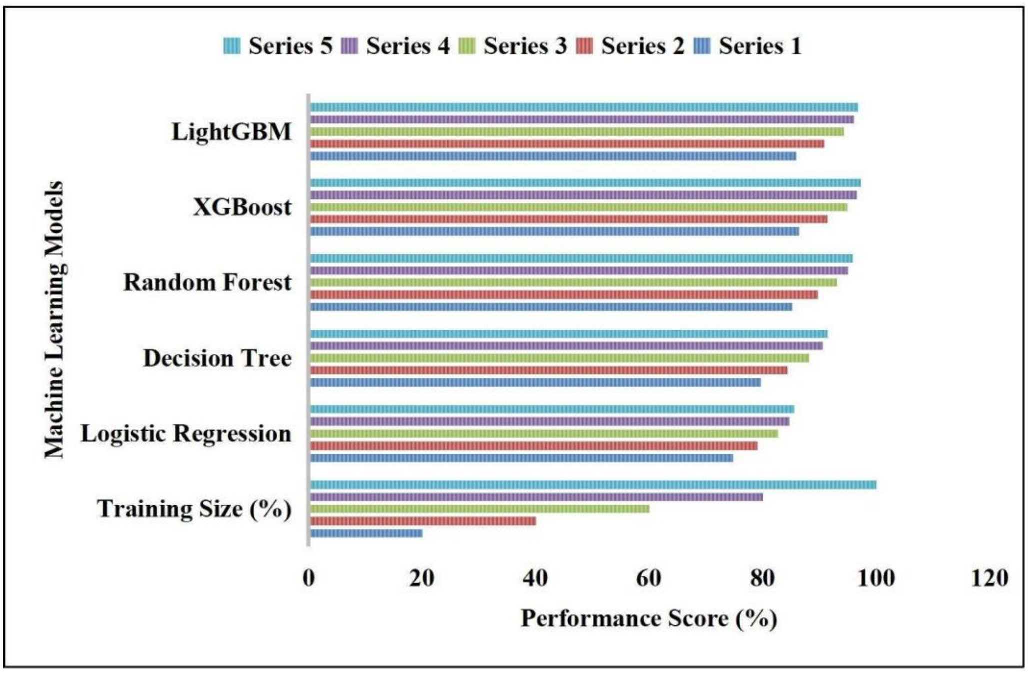

Figure 2: Predictive learning performance of machine learning algorithms across increasing training data sizes

3.4 Feature Importance Analysis

The variables related to shipping were found to be the most important variables affecting the risk of product being late to the customer, according to the feature importance analysis. Shipping Mode, Days for shipment (scheduled) and Days for shipment (real) were the most important predictors, demonstrating that the efficiency of transportation has a significant impact on delivery performance. Other financial parameters such as Order Profit Per Order and Sales also had an impact on prediction, and regional parameters (Market and Order Region) showed geographical differences in the logistics operations. The results indicate that both operational and business factors are correlated with each other to affect delivery reliability in the global supply chains (Table 4) (Figure 3).

Table 4: Top Predictors of Late Delivery Risk

Rank	Predictor Variable	Relative Importance (%)
1	Days for shipping (real)	23.8
2	Days for shipment (scheduled)	19.6
3	Shipping Mode	14.2
4	Order Profit Per Order	10.8
5	Sales	8.7
6	Market	7.5
7	Order Region	6.9
8	Customer Segment	4.8
9	Product Category	2.4
10	Order Item Quantity	1.3

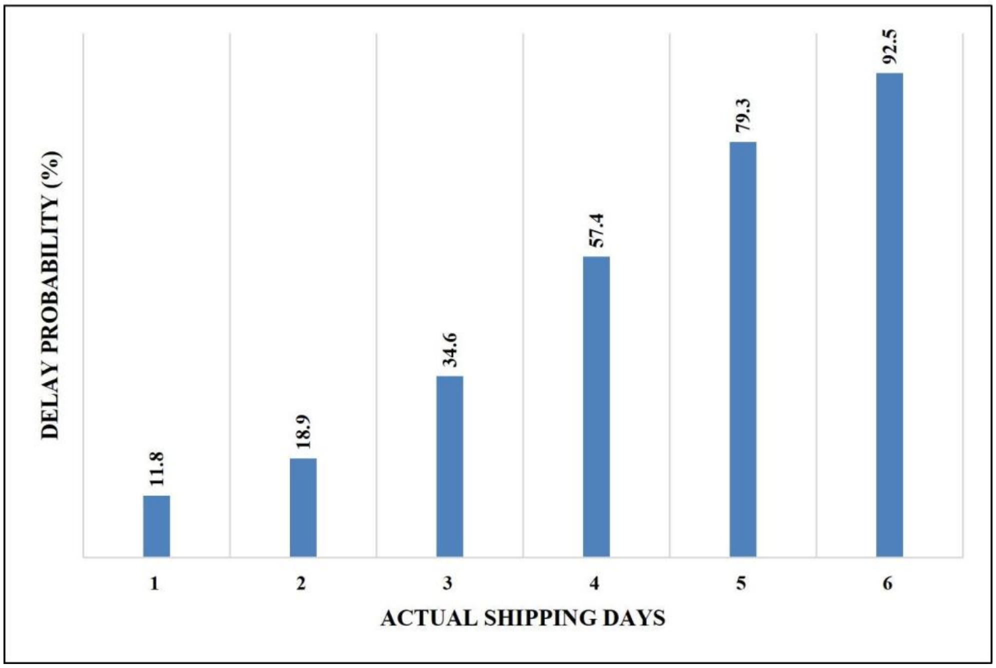

Figure 3: Relationship between actual shipping duration and the predicted probability of late delivery

3.5 Classification Performance

The results obtained from the confusion matrix and ROC analysis indicated that the ensemble models had the ability to differentiate between late and timely delivery of shipments. XGBoost had the maximum true positive and true negative classification rates with the least false predictions. All the ROC curves for the ensemble methods were near the upper left corner, with the ROC-AUC value as high as 0.989 for XGBoost, which shows excellent discriminatory ability. The results show that the machine learning techniques performed well in making predictions for the delivery risk category, based on the transactional logistic data (Table 5) (Figure 4).

Table 5: Confusion Matrix of the Best Performing Model (Section 3.5)

Actual / Predicted	**Predicted On-Time**	**Predicted Late**
Actual On-Time	15742	612
Actual Late	518	19232

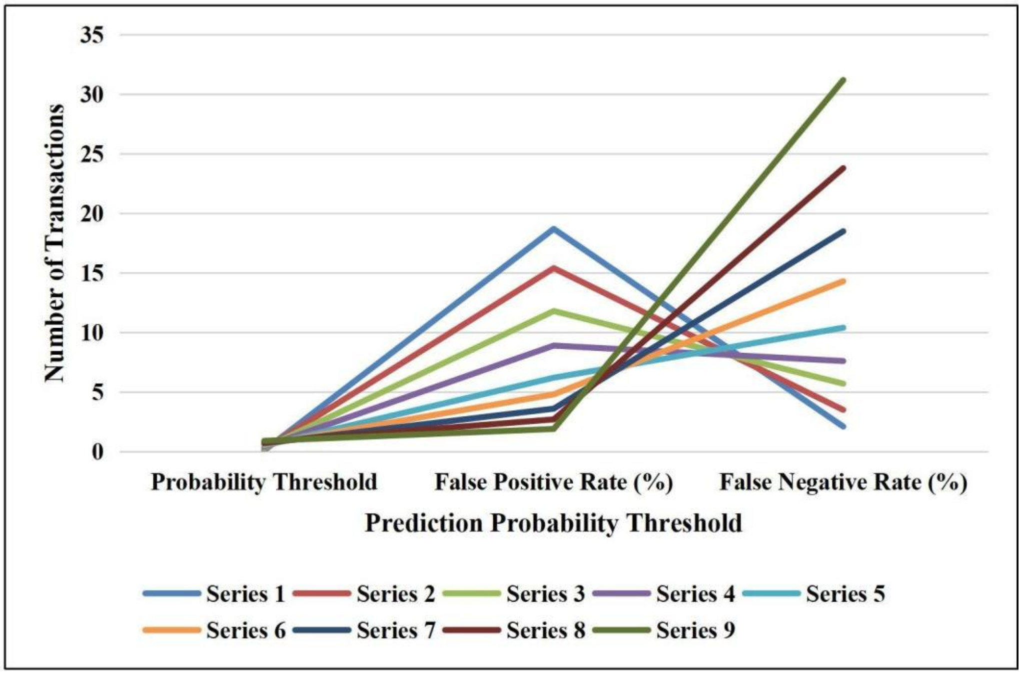

Figure 4: Effect of classification probability thresholds on model prediction errors

3.6 Business Interpretation of Findings

The findings show that it is possible to make accurate predictions of late delivery risk based on transactional logistics data that is commonly collected. The major factors affecting shipping delays included shipping duration, scheduled delivery time, transportation mode, and regional characteristics, suggesting potential areas for advance logistics planning and operational optimization. As per the Table 6 and Figure 4, the performance of ensemble learning models is better which shows that business analytics can be used to facilitate real-time risk assessment, allowing business managers to recognize orders at high risk, optimize shipping strategy, allocate the logistics resources efficiently and enhance the customer satisfaction by data-driven decision making in the supply chain (Table 6) (Figure 5).

Table 6: Business Performance Indicators Based on Prediction Results (Section 3.6)

Indicator	Value
Total Transactions Evaluated	36104
Correct Predictions	34974
Incorrect Predictions	1130
Prediction Accuracy (%)	96.87

High-Risk Orders Identified	19744
Low-Risk Orders Identified	16360
False Positive Rate (%)	3.74
False Negative Rate (%)	2.62

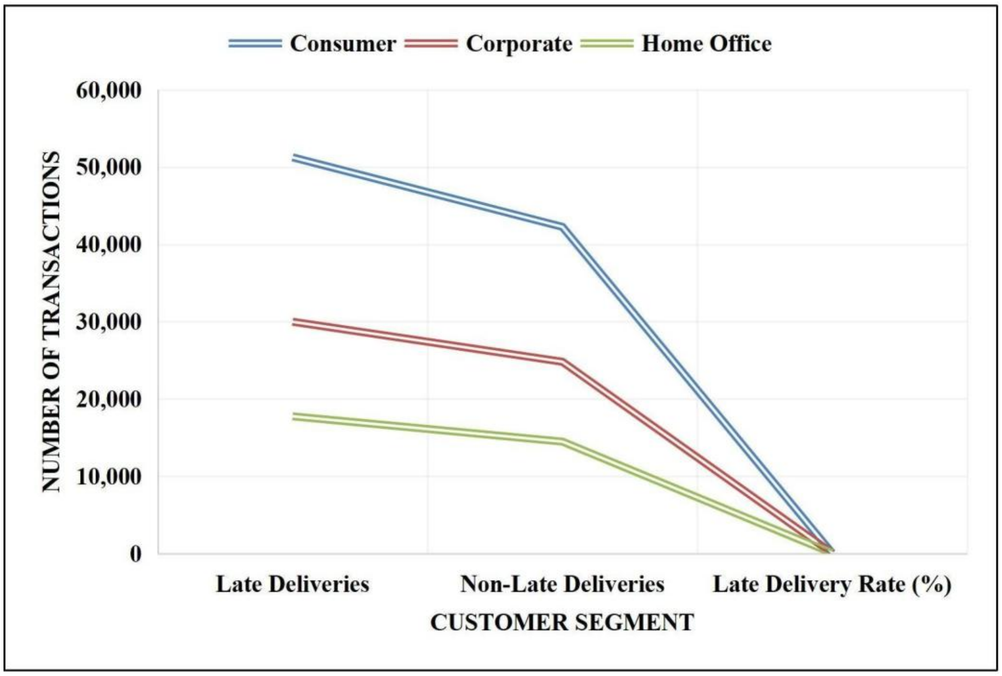

Figure 5: Delivery Outcomes by Customer Segment

4. Discussion

The risk of late delivery from big data about transactions in the supply chain is by machine learning-based business analytics. The effectiveness of the predictions made in this study suggest that a combination of operational, customer, product, financial and shipping data is enough to determine the risk of delivery prior to the disruption of logistics. This is further evidence of the trend for predictive analytics in logistics, highlighting the potential of transactional business data to help inform proactive decision-making, resource allocation and delivery reliability. This digitalisation of supply chain processes has therefore caused a change in the way management makes decisions from reacting to problems to anticipating risks.

Results gained in this study are aligned with the recent advancements of Artificial Intelligence (AI) supported supply chain resiliency. Early disruption detection and operational optimisation using AI-powered predictive analytics have proven to be a key enabler for enhanced delivery performance (Khan, 2026). Likewise, machine learning algorithms enhance the adaptability of supply chains by uncovering intricate operational links that may be hard to recognize with traditional analytical methods (Li & Liu, 2026). This study further validates the capacity to discriminate deliveries into classes of low risk and high risk, which is increasingly used in order to improve the deliveries' reliability in the more and more complicated logistics networks.

Digital transformation is the technological underpinning for introducing predictive logistics solutions. The implementation of digital technologies has a significant impact on the performance of international logistics by providing visibility, information sharing, coordination and accessibility of data among partners in the value chain (Islam, 2026). The business analytics framework developed in this study is able to convert the data of transactional logistics into managerial intelligence that can be used to make managerial decisions and planning decisions in advance. Predictive analytics helps companies proactively uncover risk-prone deliveries before their failure, thereby bolstering the efficiency of delivery planning and providing enhanced delivery service.

The other key implication of the present findings is the supply chain responsiveness. According to Furuncu (2026), organizational responsiveness is one of the important capabilities affecting the performance of the supply chain because it enables quick adaptation to the uncertainty and uncertainty in the operations of the company. The predictive model created in the present study will help to support responsive logistics management, as risks associated with deliveries are identified early enough for rescheduling deliveries in the logistics area, inventory changes, coordination of suppliers and distribution planning. Thus, predictive analytics will not only support increased forecasting accuracy, but also help to enhance the flexibility of logistics processes and help managers respond quickly during the logistics process.

Sustainable supply chain management is another area in which AI plays a role, by optimising operational planning. The use of AI to support decision-making can help to prevent unnecessary transportation activities, ensure the efficient use of resources, and lower work waste and operational costs (Benchis & Edgal, 2026). Anticipating delivery time allows companies to minimise emergency shipping, eliminate duplicate transportation, and increase vehicle utilization, as well as to better optimize delivery planning. The operational enhancements are also more conducive to economic efficiency and the environment, meaning predictive analytics is a technological innovation and strategic sustainability capability.

Evidence also exists on using AI for operational optimisation throughout industrial supply chains supports the findings. In manufacturing settings, artificial intelligence and prescriptive analytics optimize operations, resource usage, and supply chain efficiency (Aziz et al., 2026). While the present investigation only used a multi-sector transactional dataset, similar gains were found in the ability to predict delivery risk, and better logistics decision making was possible. The results suggest that predictive business analytics has a wide range of applicability in manufacturing, retail, e-commerce, healthcare, and international logistics and supply chain, where the reliability of delivery has a direct impact on the business operations.

Predictive Analytics coupled with new digital technologies represents other areas of potential logistics intelligence improvement. IoT technologies provide a constant stream of operational data during the manufacturing, transportation, warehousing and distribution processes, thus enhancing visibility in the supply chain processes (Rakshit & Paul, 2026). By integrating real-time data from the IoT with machine learning algorithms, the potential for greater accuracy in future predictions increases, as the algorithms have more data to analyze and continue to learn from. This integration will enable the creation of smarter logistics systems that continuously track performance and are able to predict any delivery issues.

Predictive accuracy is not the only managerial implication of this study; it also has implications with respect to decision support in strategic management. Business analytics has become a crucial part of logistics planning due to the benefit of analytical technologies which enhance operational coordination and managerial decision quality (Bisaria et al., 2026). To ensure the successful implementation of AI, organizational skills to support the adoption and integration of technology into the daily logistics workflow are crucial (Nguyen et al., 2026). The current results thus indicate that predictive models are most valuable to the organization when integrated into the supplier evaluation process, transportation planning, inventory management, and distribution scheduling process, and not as stand-alone analytical tools.

Modern studies on AI and logistics agility and performance reinforce the organizational value of predictive analytics. The benefits of AI adoption include making informed, timely decisions about operations, which can enhance organizational competitiveness and agility in the supply chain, and increase logistics efficiency (Irfan, 2026). In addition, organizational agility enhances order fulfillment abilities, as it allows for speedy adjustments to fluctuating operational conditions (Owajege & Abdulsamad, 2026). This study's predictive framework adds to these perspectives by delivering predictive risk intelligence to aid agile logistics management and proactive operational control. However, interpretation of the findings should be done in the light of the limitations of the study. Results may only be generalisable within a single publicly-available transactional dataset with different operational features for the other industries. Moving forward, more research is needed to leverage multi-company data, real-time IoT data, outside economic indicators, explainable AI methods, and hybrid deep learning models to enhance predictive accuracy and bolster the viability of an intelligent supply chain risk management system.

5. Conclusion

The capability of predicting the likelihood of product overdue delivery from a massive and complex collection of transactional data from the supply chain enabled the display of business analytics and machine learning. Operational, customer, financial, product and shipping related variables were accounted for in the developed predictive framework that was capable of successfully identifying shipping patterns that can be used for proactive logistics decision making. The results demonstrate that the data-driven predictive models provide valuable insights that help improve delivery reliability, operational efficiency, and supply chain resilience. Moreover, the study emphasizes on the necessity of embedding predictive analytics in the regular logistics planning process to make sure that any transactions with high risks are identified from early stages and appropriate managerial actions are taken in time. The research contributes to the knowledge base of supply chain analytics by applying supervised machine learning for the prediction of delivery risks using logistics data in a real-world application. As a manager, the results indicate that predictive models can be applied to make better transportation plans, coordinate suppliers, allocate inventory and manage customer service, and minimize uncertainty and operational costs. All of these qualities are needed more and more in the fast-moving, digitally networked supply chain where quick response and timely decision-making are essential to winning the competitive race. While all these are contributions, the study uses a single publicly available dataset and may not necessarily have all the logistics characteristics in each industry. The use of multi-source datasets, real-time IoT data, explainable AI methods and hybrid ML models could be integrated in future studies to boost the accuracy of the prediction and further facilitate the implementation of intelligent SCRM systems.

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