SXI++: An AI-Driven Framework for Enhancing Supply Chain Efficiency and Optimization

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Abstract: Supply chain disruptions, including backorders and shipment delays, significantly impact operational efficiency, customer satisfaction, and financial performance. Traditional forecasting methods often struggle with imbalanced data, dynamic demand fluctuations, and logistical uncertainties, making it challenging to predict and mitigate disruptions effectively. Machine Learning (ML) models have emerged as promising solutions for supply chain risk management, yet many suffer from limitations in accuracy, adaptability, and interpretability. In this study, we propose the SXI++ framework as an advanced predictive solution, offering high accuracy, actionable insights, and enhanced supply chain decision-making capabilities. The SXI++ algorithm is a dynamic scoring system that converts complex, multidimensional supply chain data into actionable insights by leveraging composite scores/weights from multiple machine learning and deep learning models. By integrating a proprietary deep neural network, the model refines its predictive correlations with supply chain outcomes, achieving better accuracy while providing interpretable pathways to optimize logistics and inventory management. This study utilizes a dataset comprising 250,000 records for backorder and 30,101 records for shipment delay analysis. Key features include supplier performance, forecasted demand, past sales trends, shipment tracking data, geographical factors, and courier performance metrics. Missing values were imputed using advanced statistical techniques to ensure data integrity. The SXI++ framework employs iterative calibration, dynamic weight adjustments, and deep neural network modeling to enhance predictive accuracy. Performance metrics, including accuracy, precision, and AUC, were calculated to evaluate the model's effectiveness. Additionally, decision tree analyses were conducted to provide interpretable pathways for reducing backorders and shipment delays, identifying critical operational factors and targeted optimization strategies. The SXI++ algorithm demonstrated superior predictive capabilities, achieving an accuracy of 99.48% for backorder prediction and 99.60% for shipment delay classification, significantly outperforming traditional ML models. Precision and AUC scores reached 97.10% and 0.99, respectively, underscoring the model's reliability. The study established a strong correlation between optimized SXI scores and improved supply chain performance, with a 30.05% reduction in SXI scores resulting in an 87.71% decrease in backorders, while a 9.23% increase in SXI scores led to an 85.13% reduction in shipment delays. Decision tree analyses identified key factors influencing supply chain inefficiencies, such as supplier lead times, forecast accuracy, and transportation constraints, providing actionable recommendations for improvement. The SXI++ platform predicts supply chain risks with near-perfect accuracy and precision using deep learning architectures and iterative calibration. Its ability to direct targeted actions and improve supply chain operations is highlighted by its substantial correlation with reduced backorders and shipment delays. In contrast to conventional models, supply chain managers may proactively reduce risks, optimize logistics, and boost overall efficiency with SXI++'s interpretable decision tree paths.

Keywords: backorders, shipment delays, stockouts, logistic and transportations, supply chain optimization, SXI++, Deep Neural Networks (DNN), predictive modelling

1. Introduction

Supply Chain Management (SCM) is the systematic coordination of activities and operations within an organization to enhance efficiency and integration. The goal is to streamline procurement, enhance overall efficiency, and improve customer satisfaction. Any business operation depends on Supply Chain Management (SCM), and even small mistakes or inconsistencies in data can cause serious problems for end users [1, 2]. For instance, displaying incorrect inventory information online or marking products as unavailable during checkout can frustrate customers, damage brand perception, and result in revenue loss or negative online feedback. Therefore, to guarantee a satisfying experience for customers and maintain the company's reputation, it is essential to maintain accuracy and near real-time data in supply chain activities [3]. An important function of SCM is supplier selection, where procurement managers evaluate and choose optimal raw material providers. Finding the correct suppliers can lower procurement costs, improve operational performance, and establish long-term positive relationships—all of which will eventually raise customer satisfaction. Similarly, production planning—deciding what products to offer based on market needs and company capacity—is a key SCM activity [4, 5].

Proper inventory management is necessary to match supply with demand, reduce excess holding costs, and prevent stock shortages. Efficient SCM enables smooth goods movement across markets, reduces costs, boosts efficiency, and supports long-term financial stability. The importance of selecting the right suppliers is also evident, as poor supplier decisions can cause financial difficulties and lower overall organizational performance.

A backorder refers to a situation where a product is temporarily unavailable, and customers agree to receive it later when stock is replenished. Backorders are typically observed when products are unavailable due to high demand or anticipated future releases. For example, the COVID-19 pandemic triggered unusually high demand for sanitizers and home-use items, producing a bullwhip (Forrester) effect across multiple sectors as companies failed to anticipate the surge [6]. Backorders play a crucial role in inventory management since they directly affect production and supply chain costs. Numerous studies in the literature have examined the Economic Order Quantity (EOQ) and Economic Production Quantity (EPQ), incorporating the effects of backorders [7–10].

These approaches include: (i) coordinating and minimizing the total supply chain costs, factoring in backorders [11, 12] , and stochastic supply variations [13, 14]; (ii) solving inventory-related problems involving backorders [15–18] and safety stocks [19], optimization models for different backorder scenarios [20–22], while also considering aspects like human errors [23], customer preferences [24, 25], and sustainability objectives [26]; (iii) applying fuzzy logic for demand and order modeling [27–29]; and (iv) using heuristic methods to optimize inventory systems [30–32]. Given the cost implications of backorders, predictive modeling has become a key research direction. Machine learning and AI techniques are particularly used to handle data imbalance, as the number of backordered items is much lower than that of in-stock items [33].

In a study on backorder prediction, eight machine learning models were evaluated comparatively. Among these, the RF, XGB, LGBM, and BB models demonstrated similar performance, each achieving an AUC score of 0.95. Most classifiers reached an accuracy of up to 88.85%, whereas KNN (Accuracy = 75.93%, Precision = 74.30%), LR (Accuracy = 70.22%, Precision = 69.04%), and SVM (Accuracy = 72.39%, Precision = 67.85%) showed lower accuracy, with a maximum of 75.93%. The RF (Accuracy = 88.82%, Precision = 88.10%), XGB

(Accuracy = 88.53%, Precision = 87.38%), LGBM (Accuracy = 87.78%, Precision = 87.01%), and Balanced Bagging (Accuracy = 88.85%, Precision = 87.61%) models also excelled in other metrics such as recall (up to 90.69%), f1-score (up to 89.12%), and precision (up to 88.10%) [34].

Container shipping plays a crucial role in global trade, connecting every stage of the supply chain—from manufacturing to end consumers [35]. The past thirty years have seen sharp increases in shipping activity and vessel size [36, 37]. Yet, growing congestion at major ports and waterways like the Suez Canal already contributes to significant delays, a problem expected to escalate as the sector expands [38].

In addition to congestion, adverse weather conditions also contribute to delays in container shipping [38]. Extreme weather events, in particular, can cause major disruptions in supply chains, with transportation being especially affected [39]. Moreover, the frequency of such extreme weather events is rising globally at an alarming rate [40, 41]. Enhancing the ability to predict supply chain disruptions caused by extreme weather would greatly improve supply chain resilience [42].

Previous works look on ways to reduce the risk of disruptions to the supply chain. We focus on Supply Chain Risk Management (SCRM) in this literature review. In general, there are four primary categories into which SCRM techniques can be divided: Disruption Risk Management (DRM), Operational Risk Control (ORC), Disaster and Emergency Management (DEM), and Logistics Service Risk Analysis (LSRA) [43]. Unlike DEM and DRM, neither ORC nor LSRA take into account unexpected supply chain disruptions, such as those caused by extreme weather occurrences. Unlike DEM and DRM, neither ORC nor LSRA take into account unexpected supply chain disruptions, such as those caused by extreme weather occurrences. The objective of this study is not post-event decision assistance, which is related to DEM. Container vessel delays can be predicted as part of DRM's pre-event decision assistance. There are existing prediction models that use Bayesian networks based on fuzzy rules as a hybrid decision method [38]. A prediction model using data mining and the machine learning algorithm random forest is presented in further research [10]. Additionally, a comparison analysis of two container terminals provides qualitative delay estimates derived from machine learning techniques such random forest [44]. Another machine learning approach, neural networks, is used to predict delays in order to more precisely forecast the number of human resources needed to cover daily port operations [45]. Similarly, data mining research proposes a Classification and Regression Tree (CART) model for more effective human resource allocation at ports [46]. All existing DRM research primarily targets the operational planning level, thereby restricting improvements to terminal operations. On the other hand, at the strategic planning stage, services are directed toward key participants in the shipping chain, including senders, recipients, terminal operators, and carriers.

Researchers have previously proposed various techniques to address and lower the impact of disruptions within supply chains. This literature review specifically examines supply Chain Risk Management (SCRM). Broadly, SCRM strategies can be categorized into four main areas: Disruption Risk Management (DRM), Operational Risk Control (ORC), Disaster and Emergency Management (DEM), and Logistics Service Risk Analysis (LSRA) [9]. Among these, ORC and LSRA exclude unforeseen disruptions such as those triggered by severe weather, whereas DRM and DEM address them. As DEM focuses on decisions made after a disruption, it is excluded from this analysis.

DRM, on the other hand, provides pre-event decision support by predicting container vessel delays. Existing prediction models utilize a hybrid approach combining fuzzy rule-based Bayesian networks [38]. In a separate study, data mining techniques along with the Random Forest ML model were employed for predicting delays [43]. Additionally, ML-based qualitative delay estimates, including random forest, have been analyzed through a comparative study of two container terminals [44]. Neural networks, another ML approach, have been used to forecast vessel delays and improve workforce planning for daily port operations [45].

Previous studies have primarily leveraged machine learning techniques to address the challenges of predicting shipment delays and backorder risks, particularly in identifying high-risk shipments and inventory shortages within supply chain operations. However, these studies often encountered difficulties in interpreting and explaining the influence of various logistical, demand, and inventory factors on shipment delay and backorder predictions, assessing improvements in reducing delays and stockouts over short-, mid-, and long-term periods, or implementing a comprehensive model capable of predicting both shipment delays and backorders without extensive prior training.

To address these gaps, this study focuses on:

(i) Evaluating the performance of the SXI++ algorithm as a multivariate scoring system for predicting shipment delays and backorders as binary classification problems.

(ii) Enhancing the SXI++ scoring methodology through the Proprietary Deep Neural Network algorithm and correlating it with shipment delay reduction and backorder prevention rates across three timeframes: Immediate, Mid-term, and Long-term.

(iii) Employing a targeted decision tree framework to interpret the most effective pathways leading to delayed/on-time shipments and backorder/no-backorder scenarios. This framework identifies critical logistical factors such as pickup location type, shipment volume, supplier lead time, and demand variability, providing actionable insights for optimizing supply chain efficiency. By exploring the predictive pathways for shipment delays and backorders, the study establishes a unified model capable of identifying overlapping risk factors, significantly improving logistics management, inventory control, and operational decision-making.

2. Materials and Methods

2.1. Backorder Dataset Description

This study utilizes a real-world imbalanced dataset containing historical inventory records of active products over the eight weeks preceding the prediction period. The dataset comprises approximately 1.9 million entries with 23 attributes, including product identifiers, inventory levels, sales and forecast metrics, supplier performance indicators, and backorder status.

For our analysis, we extracted a sample of 200,000 records from this dataset for training and validation purposes, and a separate set of 50,000 records was reserved for blind test predictions.

The target variable indicates whether a product went on backorder, with around 3.7% of SKUs labeled as backordered.

2.2. Shipment Dataset Description

The dataset contains 30,101 records with 36 features (Table 1) related to shipment deliveries, tracking delays, and logistics factors. The target variable, is delayed, indicates whether a shipment was delayed (1) or delivered on time (0). The dataset is imbalanced, with 5,101 delayed shipments and 25,000 non-delayed shipments.

The features capture a wide range of factors influencing shipment delays, including geographical data, Service Level Agreements (SLAs), shipment order types, fulfilment center information, and past courier performance metrics. The dataset is structured to analyze how different logistical, geographical, and operational factors contribute to shipment delays.

Table 1. Shipment Dataset Feature Description

Feature Name	Description
Shipment_id	Id of the shipments
actual_TAT	Actual turnaround time for shipment delivery.
SLA	Service level agreement (expected delivery time commitment).
pickup_lat	Latitude of the pickup location.
pickup_lon	Longitude of the pickup location.
drop_lat	Latitude of the drop-off (delivery) location.
drop_lon	Longitude of the drop-off (delivery) location.
distance	Distance between pickup and drop-off locations (in km).
drop	if the drop-off location is in a metro city or not
pickup_metro	if the pickup location is in a metro city or not
cp_delay_quarter	Count of delayed shipments handled by the courier partner in the quarter.
cp_ontime_quarter	Count of on-time shipments handled by the courier partner in the quarter.
cp_delay_per_quarter	Percentage of delayed shipments for the courier partner in the quarter.
cp_ontime_per_quarter	Percentage of on-time shipments for the courier partner in the quarter.
cp_pincode_served_quarter	Number of unique pincodes served by the courier partner in the quarter.
cp_pincode_served_percent_quarter	Percentage of pincodes served relative to total serviced areas in the quarter.
cp_avg_score_quarter	Average performance score of the courier partner in the quarter.
cp_pos_score_quarter	Positive feedback score for the courier partner in the quarter.
cp_neg_score_quarter	Negative feedback score for the courier partner in the quarter.
cp_delay_month	Count of delayed shipments handled by the courier partner in the month.
cp_ontime_month	Count of on-time shipments handled by the courier partner in the month.
cp_delay_per_month	Percentage of delayed shipments for the courier partner in the month.
cp_ontime_per_month	Percentage of on-time shipments for the courier partner in the month.
cp_pincode_served_month	Number of unique pincodes served by the courier partner in the month.
cp_pincode_served_percent_month	Percentage of pincodes served relative to total serviced areas in the month.
cp_avg_score_month	Average performance score of the courier partner in the month.
cp_pos_score_month	Positive feedback score for the courier partner in the month.
cp_neg_score_month	Negative feedback score for the courier partner in the month.
fc_name	Name of fulfillment center
fc_city	City where the fulfillment center is located.
shipment_weight	Weight of the shipment package (in kg or g).
shipment_order_type	If shipment is cash-on-delivery (COD) or prepaid.
shipment_box_type	Type of box used for shipment (e.g., small, medium, large, fragile).
pickedup_week_day	Day of the week when the shipment was picked up.
pickedup_day	Day of the month when the shipment was picked up.
pickup_time	Time of the day when the shipment was picked up.

2.3. SXI++ Model Framework

The SXI++ is a dynamic scoring system that reduces difficult, multidimensional problems to a simpler, two-dimensional answer. It generates a weighted composite score that represents the most important factors influencing supplier performance, shipment delays, and inventory management, from five to ten machine learning algorithms. SXI++ improves its association with important supply chain outcomes by iteratively modifying these weights using a proprietary deep neural network, increasing prediction accuracy. Decision-making is then optimized using this score, which can reduce shipment delays, minimize backorders, and increase supply chain efficiency overall.

The SXI++ framework consists of the following steps:

1) Pre-processing and Normalization
2) Bivariate Correlation Analysis
3) Base SXI++ Score Calculation
4) LASSO Regression Adjustment
5) Composite Weight Calculation and Final SXI Score
6) Benchmark Analysis
7) Comparison with Delineation

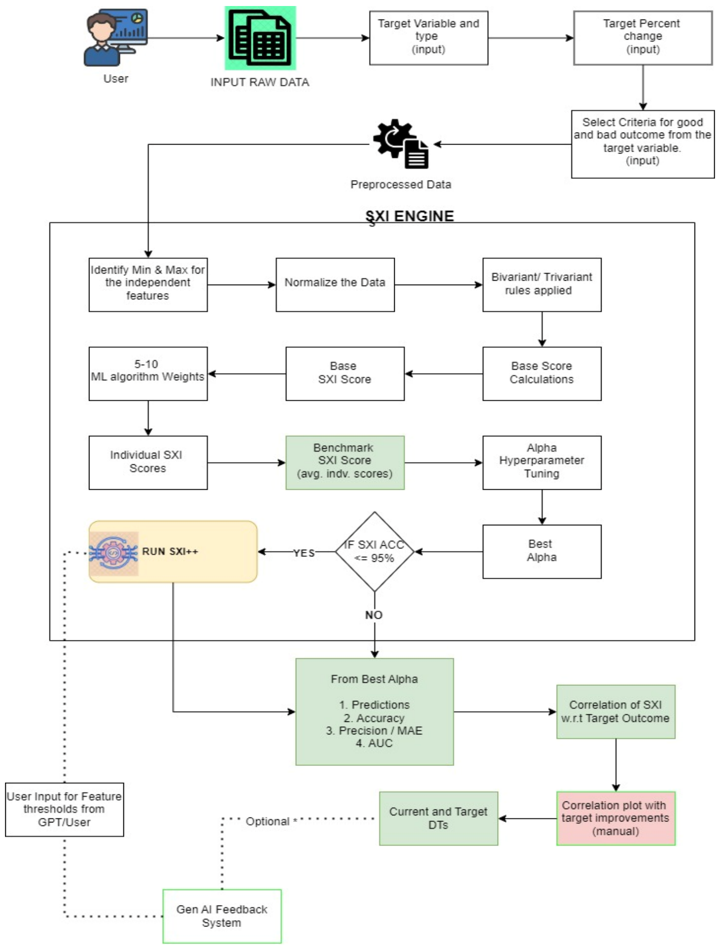

Fig. 1. SXI++ LNM framework.

The SXI++ framework depends on a deep neural network, which lends itself to an iterative weight calculation step. These steps are shown in Fig. 1. [47].

2.3.1. Correlation of SXI++ w.r.t supply chain outcomes

In terms of business results, this score can be associated with particular categories like "good" and "bad" in the dataset. A frequently used measure for assessing the strength of this association is the coefficient of determination, typically referred to as R-squared (R^2).

When SXI scores (x) serve as the independent variable and the target outcome (y) as the dependent variable, the relationship can be represented by a polynomial regression equation.

$$y = b_0 + b_1 x + b_2 x^2 + \cdots + b_n x^n + \in$$

where:

y is the target outcome.

x is the SXI scores.

$b_0, b_1, b_2, \ldots, b_n$ are the coefficients representing the weights of the polynomial terms.

n is the degree of the polynomial.

$\in$ is the error term.

The coefficient of determination, known as R^2, measures the extent to which SXI scores account for variability in business results. Three different improvement phases—immediate, mid-term, and long-term improvements—can be distinguished by examining polynomial regression plots. These phases clarify where alterations in SXI scores most notably influence supply chain results, assisting in the strategic analysis of data trends and patterns.

Short-Term (Immediate) Improvement: This initial stage is defined by a clear, positive impact on SXI scores, which becomes apparent within the first few months of implementing changes.

Mid-Term Improvement: The subsequent stage involves a consistent, upward trend in SXI scores over a period lasting from three to twelve months.

Long-Term Improvement: This final phase is reached when the SXI scores either stabilize at a high level or continue to show gradual enhancement for a year or more.

2.3.2. Model training and evaluation

The process of training the model begins with the tuning of hyper parameters, with a particular emphasis on the alpha parameter. This involves altering the alpha value in steps of 0.1 between 0.5 and 1.5 in order to adjust the SXI score. The specific steps involved are described in [3].

Several criteria are used to fully assess the model's performance. Accuracy indicates the overall correctness of the model's predictions, whereas precision highlights the ratio of true positive outcomes relative to all positive forecasts. The confusion matrix provides a comprehensive overview of true positives, true negatives, false positives, and false negatives, offering further insight into the model's classification performance. Furthermore, the model's ability to differentiate between classes is evaluated using the Area Under the Curve (AUC), which is a reliable measure of its prediction ability.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision/PPV = \frac{TP}{TP + FP}$$

$$Recall/NPV = \frac{TP}{TP + FN}$$

where:

- TP represents the count of true positives.
- TN represents the count of true negatives.
- FP represents the count of false positives.
- FN represents the count of false negatives.

The AUC Score is essentially a single performance measure that shows how well a model can separate two groups. This score is calculated from the ROC curve, a graph that shows the trade-off between two things:

- How many true positives (correctly identified positives) the model catches.
- How many false positives (incorrectly identified positives) the model makes.

$$TPR = \frac{TP}{TP + FN}$$

$$FPR = \frac{FP}{FP + TN}$$

$$AUC \approx \sum_{i=1}^{n-1} \left(\frac{TPR_{i+1} + TPR_i}{2}\right)(FPR_{i+1} - FPR_i)$$

where:
TPR_i and TPR_{i+1} denote true positive rates corresponding to adjacent threshold points.
FPR_i and FPR_{i+1} denote false positive rates corresponding to adjacent threshold points.

2.3.3. Actionable insights for improving supply chain efficiency

In the decision tree model for optimizing supply chain outcomes, key operational features that increase the likelihood of inefficiencies, such as delays or stockouts, are assigned positive weights, while those that reduce inefficiencies, such as optimized inventory levels or reliable supplier performance, are assigned negative weights. To implement strategies for minimizing disruptions and improving efficiency, users can specify the percentage increase for features with positive weights (indicating higher risk of inefficiencies) and the percentage decrease for features with negative weights (suggesting lower risk). Throughout data transformation, modifications are implemented at the observation level: features with positive weights undergo percentage-based increases, whereas those with negative weights are reduced proportionally. This approach strengthens the dataset's predictive capability for optimizing supply chain operations.

When the model demonstrates a positive association between SXI scores and supply chain inefficiency probability, positively weighted features are modified according to:

Adjusted Feature Value = Original Feature Values × (1 + Percentage)

Conversely, negatively weighted features undergo adjustment using:

Adjusted Feature Value = Original Feature Values × (1 - Percentage)

In contrast, when the model identifies a negative association between SXI scores and supply chain inefficiencies (indicating certain features contribute to greater efficiency), the weighting approach is inverted. Under these conditions, positively weighted features—which signal elevated inefficiency risk as their values rise—are reduced by the designated percentage, whereas negatively weighted features—which indicate diminished risk with increasing values—are amplified by the same percentage.

After implementing these transformations, the modified dataset serves as input for training a Random Forest model limited to a maximum depth of 4. This setting regulates the model's complexity, enabling it to detect varying degrees of data granularity. Deeper trees can identify more complex relationships, whereas shallower ones produce more straightforward models that offer improved generalization, though they might overlook subtle details. Here, a depth of 4 provides an optimal compromise between complexity and generalization

Random Forest modelling evaluates how operational features influence supply chain effectiveness through numerous decision trees working in concert. Each tree detects specific trends within the data, leading to the identification of an optimal target decision tree trajectory. This trajectory outlines the progression of feature separations that most precisely anticipates supply chain efficiency challenges or gains based on transformed data inputs. This framework enables deep comprehension of driving factors while supplying concrete strategies for addressing risks, enhancing logistical operations, and elevating supply chain efficiency standards.

3. Results

3.1. Backorders

The delineation of SXI reveals that all backorder SKUs are above the SXI threshold (Fig. 2), constituting

6.87%, while all SKUs that are not backorders fall below SXI are at 99.13%. In terms of the overall class, backorders above SXI represent 3.24% of the total, while not backorders below SXI make up 52.33%. The model evaluation indicates a training size of 144,000, validation size of 20,000 and a test size of 36,000, totaling 200,000 instances. Among the test cases, all 35,713 SKUs were correctly predicted as backorder or not, yielding an SXI accuracy of 99.16%.

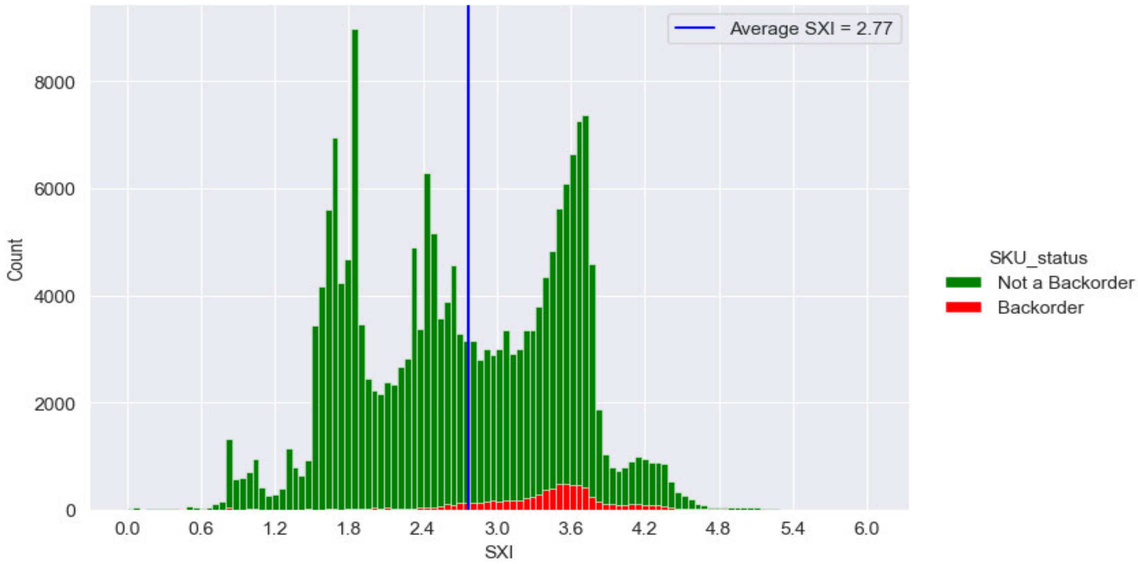

Fig. 2. SXI distribution—backorders.

SXI and Backorders have an extraordinarily strong and positive link, as shown by the correlation coefficient of 1 (positively) between these two variables (Fig. 3). In practice, this means that when the SXI score rises, Backorders rise proportionally and in a significantly positive manner. According to the correlation, the SXI hypothesis states that the higher the SXI, the greater the chance of backorders; hence, a lower SXI score should result in fewer backorders.

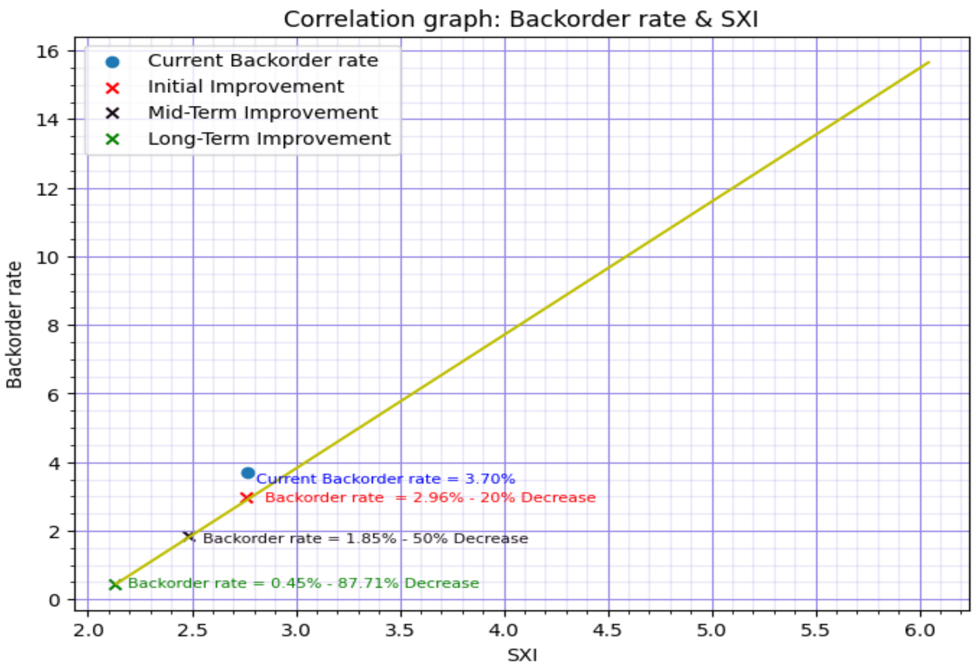

Fig. 3. Correlation: SXI vs backorder.

More precisely, a 20% decline in backorders occurs in proportion to an initial 0.36% drop in SXI scores. Going into the mid-term, a 50% drop in Backorder is equivalent to an 11.69% drop in SXI scores. In the long run, a significant 87.71% reduction in the probability of backorders is linked to a 30.05% drop in SXI ratings (Fig. 4). This illustrates the compounding effect of long-term enhancements in company results, supporting the idea that a consistent effort to lower the SXI can result in notable gains and lessen the impact of backorders.

Table 2. Performance Metrics Table—Backorders

Metrics	LR	SVM	LGBM	BB	XGBoost	SXI++
Accuracy	70.22%	72.39%	87.78%	88.85%	94.42%	99.48%
Precision	69.04%	67.85%	87.01%	87.61%	75.45%	97.10%
AUC	0.79	0.83	0.95	0.95	0.70	0.99

Table 2's performance data reveal that the SXI++ algorithm delivers superior results compared to conventional machine learning techniques across all key metrics—accuracy, precision, and AUC. SXI++ achieves an exceptional accuracy rate of 99.48%, marking improvements ranging from 5% to 42% when benchmarked against traditional methods including Logistic Regression (LR), XGBoost, LightGBM (LGBM), Balanced Boosting (BB), and Support Vector Machines (SVM). In terms of precision, SXI++ records an impressive 97.10%, exceeding both XGBoost and other established ML models referenced in prior research. Furthermore, SXI++ attains an AUC value of 0.99, demonstrating clear advantages over LGBM and BB (both at 0.95) and substantially outpacing LR's 0.79 AUC score.

3.2. Shipment Delays

The SXI benchmark stands at 2.6 (Fig. 4), serving as the threshold score for evaluating shipment delays. Among the overall shipments, 16.95% experience delays, while 83.05% are delivered on time. Based on the benchmark SXI score, 32.48% of shipments fall below 2.6, representing a significant portion of delayed shipments. Specifically, 9.73% of the total 16.95% delayed shipments are found below the SXI threshold, reinforcing the association between lower SXI scores and higher likelihood of delays. Conversely, 62.83% of the total 83.05% on-time shipments have SXI scores above 2.6, indicating that higher SXI scores correspond to improved shipment performance. This distribution highlights a negative correlation, where an increase in the SXI score is associated with a reduction in shipment delays.

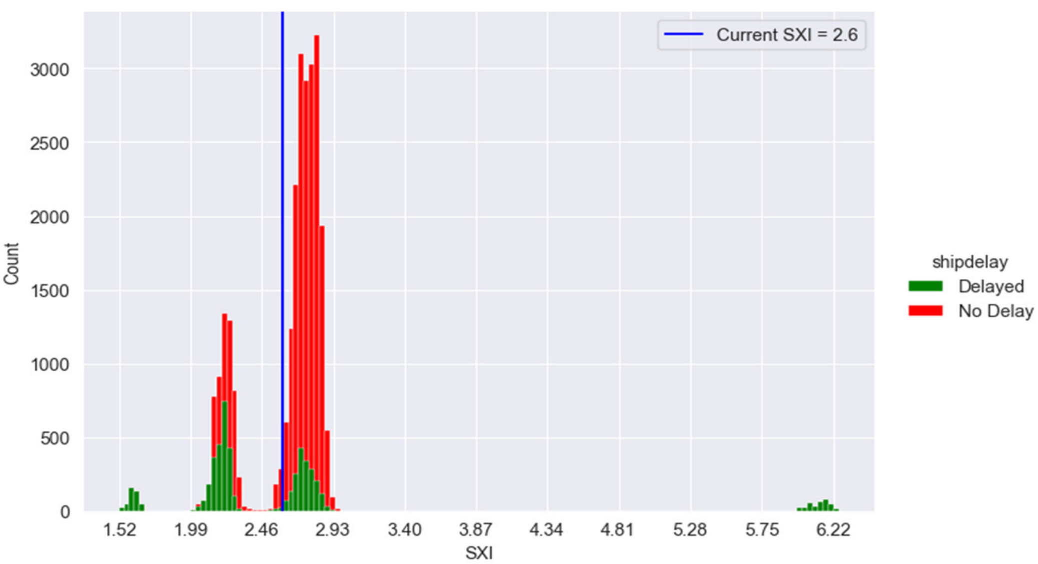

Fig. 4. SXI distribution—shipment delays.

SXI and shipping delay have an extraordinarily significant negative link, as shown by the correlation coefficient of 0.98 (negatively) between these two variables (Fig. 5). In practice, this means that shipment delays decrease proportionately and significantly as the SXI score rises. Improving the SXI score should lead to fewer delayed shipments.

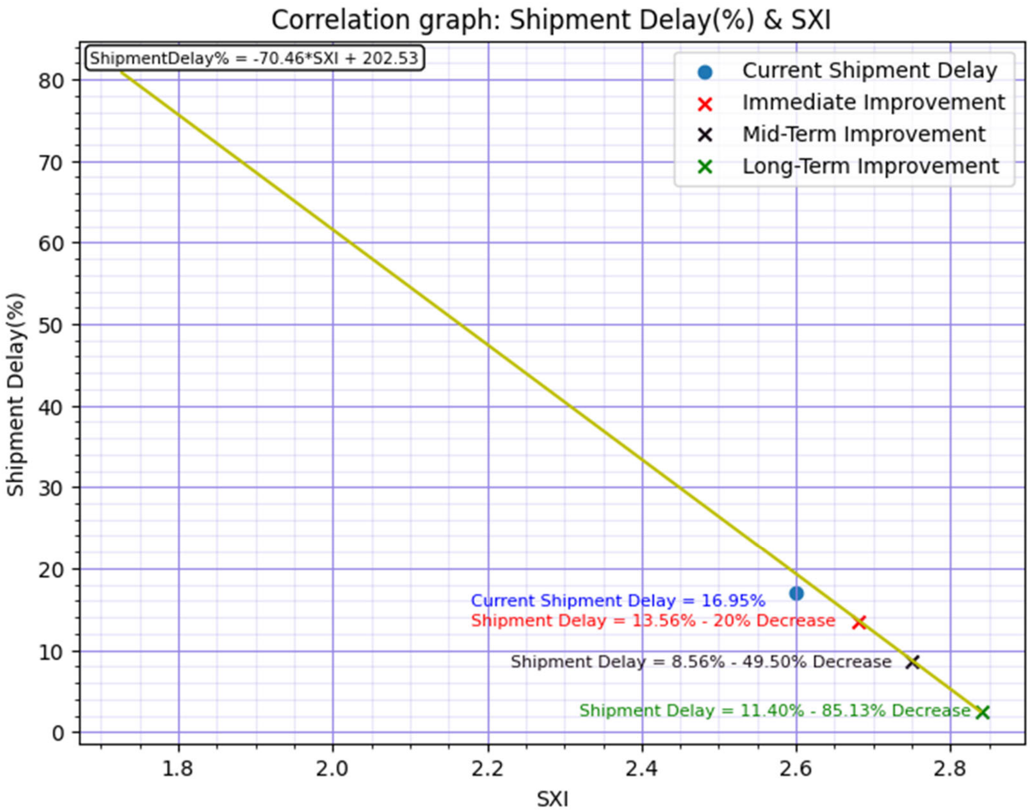

Fig. 5. Correlation—SXI vs shipment delay.

When the SXI score improves by 3.08% initially, shipment delays decrease by 20%, reducing late deliveries from 16.95% down to 13.56%. As improvements continue into the medium term with a 5.77% SXI score enhancement, delays drop by 49.50%, resulting in only 8.56% of shipments arriving late. Looking at extended timeframes, a 9.23% uplift in the SXI score generates an 85.13% decline in delayed shipments, bringing the late delivery rate to a minimal 2.52%.

These results demonstrate the incremental yet impactful nature of sustained improvements in the SXI score. While immediate changes yield notable progress, the rate of improvement slows as the SXI score reaches its optimal range. Achieving long-term goals requires persistent optimization to overcome diminishing returns in shipment delay reductions. Nonetheless, these long-term improvements reinforce the importance of increasing the SXI score for substantial enhancements in shipment efficiency.

The target decision tree (Fig. 6) introduces recommendations aimed at reducing shipment delays by identifying key factors contributing to on-time and delayed shipments. According to this decision tree, shipments are more likely to be delayed if the pickup location has a 40% or lower probability of being in a metro city, if the longitude of the drop-off location exceeds 67.47 degrees, or if the shipment box type has a 40% or higher likelihood of being categorized as NMA (Non-Metro Applicable). These conditions indicate logistical challenges such as remote pickup locations, geographically distant drop-off points, or packaging constraints that contribute to delays.

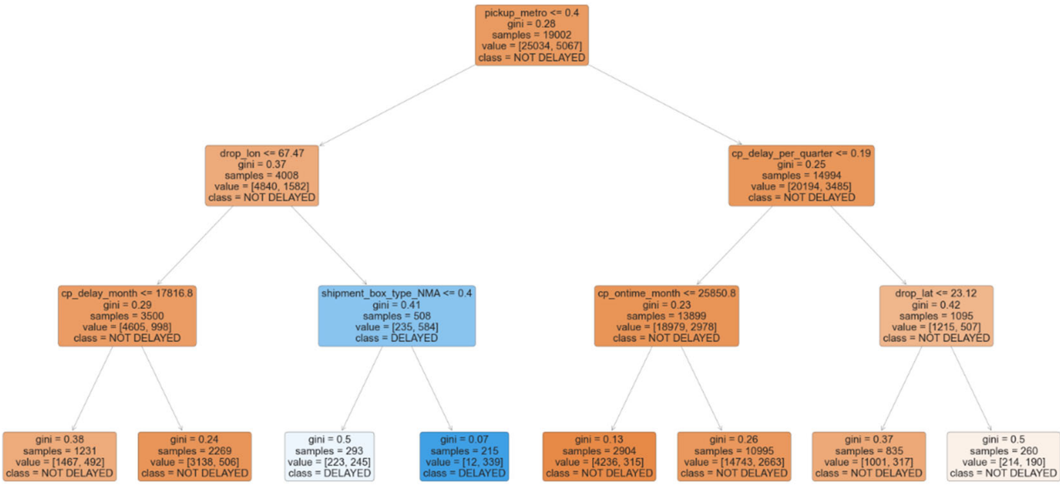

Fig. 6. Target decision tree—shipment delays.

In contrast, shipments classified as on-time are characterized by a pickup location that is at least 40% likely to be in a non-metro city, a courier partner's quarterly delayed shipment count (cp_delay_per_quarter) of less than 1, and a monthly on-time shipment count (cp_ontime_month) exceeding 25,851. These conditions highlight the influence of consistent courier partner performance and shipment volume management in maintaining timely deliveries.

The target decision tree emphasizes the key operational adjustments needed to achieve reduced shipment delays. By addressing factors such as pickup location, courier performance, and shipment box classification, the recommendations in the decision tree provide a structured approach to improving delivery efficiency. These insights underscore the importance of optimizing logistical pathways, ensuring effective courier service capabilities, and refining packaging standards to achieve significant reductions in shipment delays.

Table 3. Performance Metrics Table—Shipment Delays

Metrics	**XGBoost**	**SXI++**
Accuracy	93.15%	99.60%
Precision	92%	99.60%
Recall	95.63%	99.92
AUC	0.95	1

The SXI++ algorithm demonstrated outstanding performance (Table 3) in classifying shipment delays, significantly surpassing XGBoost across all key evaluation metrics. The dataset was divided into training (21,071 records), testing (6,020 records), and validation (3,010 records). In the test set, SXI++ correctly classified 5,996 records, with only 24 misclassifications, highlighting its exceptional precision and accuracy. Specifically, the model accurately identified 1,016 delayed shipments, with only 4 incorrectly classified as delayed shipments.

Comparing performance metrics, SXI++ achieved an accuracy of 99.60%, significantly outperforming XGBoost 93.15%. In terms of precision, SXI++ reached 99.60%, compared to XGBoost 92%. Similarly, recall for SXI++ stood at 99.92%, significantly higher than XGBoost 95.63%. Additionally, SXI++ attained an AUC score of 1, whereas XGBoost achieved 0.95, reinforcing SXI++'s superior classification capability.

4. Discussions

4.1. Key Findings

The study demonstrates the predictive capability of SXI++ models supply chain use cases such as backorder and shipment delay. In the backorder prediction task, SXI++ achieved an accuracy of 99.16%, significantly outperforming traditional machine learning models such as XGBoost, which reached 94.42%. Additionally, SXI++ (a large numerical model) further improved accuracy to 99.48%. The correlation coefficient of 1 between SXI and backorders confirms a perfect positive correlation, indicating that higher SXI scores are associated with increased backorder likelihood. Similarly, in the shipment delay prediction task, SXI++ achieved an accuracy of 99.60% and an AUC of 1.0, outperforming XGBoost, which had an accuracy of 93.15% and an AUC of 0.95. A strong negative correlation (−0.98) between SXI and shipment delays suggests that higher SXI scores correspond to a lower probability of delayed shipments.

4.2. Explanation of Findings

The exceptional predictive performance of SXI++ is attributed to their ability to leverage complex, high-dimensional relationships between independent variables and target outcomes. In the backorder use case, the SXI score effectively captures supplier performance trends, sales fluctuations, and forecast demand to accurately classify SKUs at risk of backordering. The decision tree analysis further supports these findings by identifying key thresholds such as supplier performance, sales quantities, and forecasted sales trends, which are critical indicators of backorders. Similarly, in the shipment delay use case, SXI++ effectively integrates logistical parameters, including pickup location, courier performance, and shipment classification, to determine delay likelihood. The decision tree findings emphasize that factors such as metro vs. non-metro locations, box classification, and courier service efficiency play a crucial role in predicting shipment delays.

4.3. Implications and Recommendations

The findings have significant implications for inventory management and logistics optimization. In the case of backorders, companies can proactively reduce risks by implementing supplier performance monitoring, demand forecasting adjustments, and SKU prioritization strategies based on SXI scores. A reduction in SXI scores by 30.05% is shown to correspond with an 87.71% decrease in backorders, indicating that targeted interventions can substantially mitigate backorder risks. Similarly, for shipment delays, businesses can optimize their logistics networks by focusing on key factors identified in the decision tree, such as improving pickup location efficiency and selecting courier partners with consistent performance records. Given that a 9.23% increase in SXI scores leads to an 85.13% reduction in shipment delays, strategic interventions can significantly improve delivery efficiency. Organizations should integrate SXI-based monitoring into their supply chain processes to enhance operational resilience.

4.4. User Interaction and System Integration

For practical implementation, businesses can incorporate SXI++ into real-time decision-making systems through dashboards and automated alerts. Supply chain managers can leverage these insights to prioritize high-risk SKUs, optimize order fulfillment, and minimize delays by selecting optimal transportation routes. Additionally, integrating SXI++ based predictions into Enterprise Resource Planning (ERP) and Warehouse Management Systems (WMS) can enable automated decision-making processes that improve responsiveness and efficiency in handling supply chain disruptions

4.5. Limitations and Future Investigation

Despite the promising results, certain limitations must be considered. The SXI++ models are highly dependent on the quality and availability of input data, meaning that incomplete or inaccurate records could affect prediction reliability. Additionally, while SXI++ has demonstrated high performance across both use cases, its scalability to more complex and larger datasets in different industries requires further validation. Future research should focus on expanding SXI++'s application to broader supply chain challenges, including demand forecasting under dynamic market conditions, supplier risk assessment, and real-time shipment tracking enhancements.

5. Conclusion

In this study, we comprehensively evaluated the efficacy of the SXI++ framework for supply chain optimization, focusing on backorder prediction and shipment delay reduction. By leveraging advanced deep neural network architectures with dynamic weight adjustment and hyperparameter optimization, the SXI++ algorithm demonstrated significantly superior predictive performance compared to conventional models. The framework's iterative calibration resulted in remarkable performance metrics, achieving near 99% accuracy and exceptional precision in identifying high-risk backorders and delayed shipments.

Our findings established a strong correlation between optimized SXI scores and improved supply chain outcomes, highlighting the potential of targeted interventions to achieve substantial operational improvements. The study revealed that a reduction of 30.05% in SXI scores led to an 87.71% decrease in backorders, while an increase of 9.23% in SXI scores resulted in an 85.13% reduction in shipment delays. Additionally, the decision tree analysis identified key supply chain risk factors, such as supplier performance, forecasted sales, and courier efficiency, which play a critical role in predicting disruptions. The SXI++ model outperformed traditional machine learning models, including XGBoost and LGBM, achieving a higher accuracy rate of 99.48%, a precision of 97.10%, and an AUC score of 0.99, making it the most reliable predictive tool in this study.

Performance comparisons with traditional models underscored the advantages of the SXI++ algorithm. While some machine learning models excel at capturing individual risk factors, they often struggle with imbalanced data or fail to provide interpretable insights. A key strength of the SXI++ framework lies in its ability to generate actionable decision tree pathways, which are invaluable for aiding supply chain managers in decision-making processes. These pathways offer clear insights into critical factors influencing backorders and shipment delays, such as supplier performance, lead times, and transportation constraints. This interpretability bridges the gap between complex machine learning models and practical business strategies, ensuring the framework's utility in optimizing supply chain operations.

Finally, rigorous validation on unseen datasets demonstrated the consistency of SXI++ in predicting supply chain disruptions, reinforcing its reliability and effectiveness across different industry settings. These findings emphasize the transformative potential of advanced predictive algorithms like SXI++ in improving inventory management, logistics efficiency, and overall supply chain resilience, encouraging widespread adoption in enterprise decision-making processes.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization, S.K..; methodology, S.K., P.Y., M.B.; software, P.Y, P.J.; validation, P.Y., P.J.; formal analysis, M.B., P.Y.; investigation, P.Y., P.J.; resources, S.K., M.B.; data curation, S.K., P.Y.; writing—draft preparation, P.J.; writing—review and editing, S.K., M.B., P.Y., P.J.; visualization, P.J. All authors had approved the final version.

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