AI-Driven Supply Chain Management in the United States: Machine Learning for Predictive Analytics and Business Decision-Making

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Abstract

The growing complexity of the global supply chains, the dynamic market environment, and expedited digitalization require the use of sophisticated data-driven models of operational forecasting and decision-making. This paper presents a proposed AI supply chain management predictive analytics framework based on the approaches of machine learning and deep learning to improve the predictability and business acumen of the company. Based on the LADE (Last-Mile Delivery) data set, which focuses on based on the United States of America operational data, a range of models such as Linear Regression, Random Forest, XGBoost, and a hybrid Convolutional Long Short-Term Memory (ConvLSTM) network, an assortment of models has been created and measured. The suggested ConvLSTM network combines convolutional layers of localized time-based feature extraction and LSTM layers of long-term sequential dependencies. Compared outputs prove that the ConvLSTM is better than all the baselines with the RMSE of 466.33, MAE of 234.86, and R^2 of 0.988, which reflect a good ability to predict and generalization. It has been experimentally confirmed that the hybrid architecture is effective in modeling nonlinear and dynamic relationships in the supply chain data to generate robust and accurate revenue forecasts. This study is added to the ever-expanding body of AI-powered supply chain intelligence by showing how deep sequential learning structures can be used to deliver actionable recommendations in both strategic and operational management. The next step in future studies includes incorporating more external data streams, the attention-based or transformer design, and the development of real-time decision-support systems that will enhance dynamism and performance in complicated logistics settings.

Keywords: Supply Chain Management (SCM); Predictive Analytics; Convolutional Long Short-Term Memory (ConvLSTM); LADE (Last-Mile Delivery); Data-Driven Decision-Making

Introduction:

The accelerating pace of change in global commerce, marked by frequent disruptions, shifting consumer demands, and intensifying competitive pressures, calls for more adaptive, data-intensive approaches to operations. Traditional decision paradigms anchored in static or rule-based methods are increasingly strained in volatile, interconnected environments [1], [2]. In parallel, digital transformation has opened access to large volumes of heterogeneous data: from sensor streams, enterprise resource planning (ERP) systems, procurement logs, external indicators, and evolving customer signals. This convergence of complexity and data richness presents both a challenge and an opportunity for modern enterprises [3], as illustrated in Figure 1, which depicts digital transformation as the bridge between strained traditional paradigms and adaptive, data-driven operations.

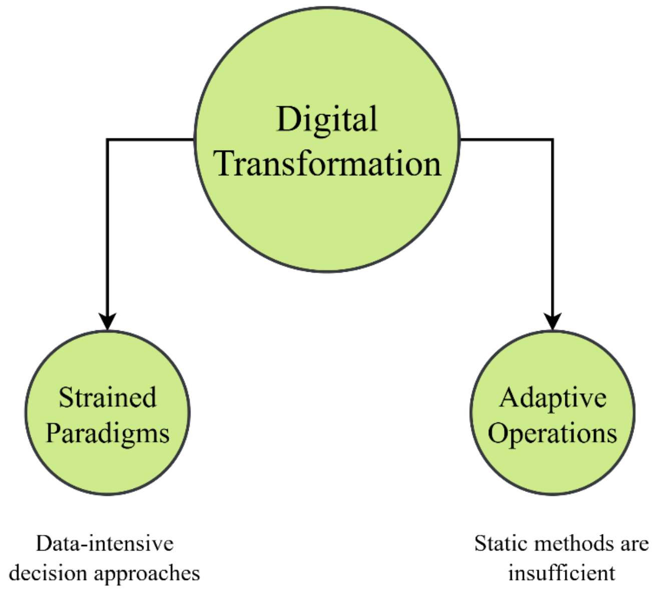

Fig. 1: Conceptual representation of the transition from traditional, rule-based decision paradigms to adaptive, data-driven operations under the influence of digital transformation.

At the heart of many industrial and commercial endeavors lies the supply chain: the interlinked network of entities, resources, processes, and flows that deliver goods and services from raw materials to end consumers. Supply chain management (SCM) encompasses planning, sourcing, production, inventory, transportation, warehousing, and return logistics, orchestrated under multiple constraints (capacity, cost, service level, risk). The efficacy of a supply chain depends on its ability to operate reliably under uncertainty, to absorb shocks, and to adapt dynamically to shifting conditions. Conventional models whether linear programming, simulation, or heuristics—often must simplify or abstract away many real-world complexities (nonlinear interactions, multi-tier dependencies, feedback loops) [4].

In recent years, the infusion of artificial intelligence (AI) and machine learning (ML) into SCM has emerged as a promising paradigm shift. Rather than relying solely on pre-specified rules or parametric assumptions, ML models can learn latent patterns and correlations from vast, multidimensional data sources. They support predictive analytics (forecasting demand, lead times,

disruptions) and prescriptive or prescriptive-analytics extensions, where model outputs guide decision recommendations (e.g., dynamic safety stock, routing adjustments, supplier allocation). AI/ML methods can ingest both structured and unstructured data, continuously retrain in response to new information, and flexibly adapt to evolving operating regimes [5].
The literature reflects growing interest in these capabilities. For instance, there is now a body of work that surveys AI applications across major supply chain functions demand forecasting, procurement, inventory control, transportation, risk management—and identifies thematic challenges around integration, interpretability, and scalability [6]. A recent systematic review of empirical studies in AI for SCM emphasizes how real-world deployments often grapple with data quality, organizational alignment, and computational constraints. Likewise, research exploring the transition from digital supply chains toward more autonomous, self-adapting systems highlights the tension between black-box model performance and the need for interpretability and trust in decision support architectures . These scholarly efforts underscore that although AI/ML promises enhanced agility, optimization, and responsiveness, realizing that promise demands careful bridging of methodological innovation and domain realities [7].

Over the past decade, the integration of Artificial Intelligence (AI) and Machine Learning (ML) into supply chain management (SCM) has gained considerable academic and industrial traction. Culot et al. [8] conducted a comprehensive systematic review outlining how AI applications have evolved from isolated forecasting tools to fully integrated decision-support systems embedded across supply chain planning, sourcing, logistics, and distribution. They emphasized that sustainable value arises when AI initiatives are connected to end-to-end business processes supported by robust data governance and strategic alignment. Similarly, Pournader et al. [9] highlighted that AI-driven supply chains are becoming central to achieving operational resilience and agility, especially in volatile and uncertain environments. Their review underscored the transformative potential of AI in enabling real-time visibility and adaptive decision-making.
In the specific domain of demand forecasting, Mediavilla et al. [10] classified AI and ML methods according to data volume, dimensionality, and prediction horizons, identifying neural networks and ensemble techniques as the most accurate approaches for high-variability markets . Douaioui et al. [11] expanded on this by comparing machine learning and deep learning techniques for demand forecasting, emphasizing the role of hybrid models that incorporate exogenous factors such as pricing, promotions, and seasonality. These studies collectively demonstrate that data preprocessing, feature engineering, and evaluation methodology have a more pronounced impact on forecasting performance than the choice of model alone.

Beyond forecasting, AI and ML are increasingly applied in logistics and transportation optimization. Tsolaki et al. [12] reviewed ML applications in freight transportation, noting successful use cases in route optimization, ETA prediction, and anomaly detection. However, they pointed out challenges such as data heterogeneity, model transferability, and the need for domain adaptation to ensure performance in real-world settings. Complementing this, Sunmola et al. [13] discussed the role of AI in building resilient supply chains, proposing frameworks for disruption prediction, real-time re-planning, and adaptive logistics networks that respond dynamically to changing conditions.

At the intersection of AI and operations research, recent studies demonstrate that reinforcement learning can outperform traditional inventory control policies under dynamic demand environments. Wu et al. [14] showed that deep reinforcement learning models can learn optimal ordering policies while accounting for stochastic lead times and variable holding costs. In addition, computer vision and ML systems have been deployed to improve warehouse operations, inventory counting, and quality control, as demonstrated by Abideen et al. [15], who found that perception-based automation reduces cycle times and errors in material handling .

Although many studies have shown the benefits of Artificial Intelligence (AI) and Machine Learning (ML) in supply chain management, there are still several important gaps that need to be addressed. Most of the existing research focuses on one part of the supply chain, such as demand forecasting [16], [17], logistics optimization [18], or inventory control [19]. However, very few studies combine these areas into an integrated and connected framework. As a result, the full potential of AI across the entire supply chain—from planning to delivery—has not yet been fully realized.

Another major gap is related to data and adaptability. Many AI models are built using specific datasets that work well for one company or one region, but fail to perform accurately when applied to new situations. Studies such as those by Mediavilla et al. [20] and Douaioui et al. [21] highlight how model accuracy depends heavily on data preparation and feature selection. In real supply chains, conditions change frequently due to market trends, disruptions, or external shocks, and models often struggle to adapt to these changes. To address these challenges this study contribute in following ways:

1. Comprehensive analysis of Supply chain management
2. Develop a robust model for revenue prediction

Methodology:

The proposed methodology involves a structured multi-stage process for developing an intelligent predictive model for supply chain performance. It begins with data collection from operational delivery records, followed by comprehensive preprocessing that includes missing value checks, feature engineering, and normalization. Exploratory Data Analysis (EDA) is then performed to uncover trends, seasonal variations, and correlations among variables. Subsequently, the dataset is divided into training and testing subsets to ensure model generalization. A sequential window creation technique (with a lookback period of seven days) is applied to transform the temporal data into supervised learning sequences. Multiple machine learning and deep learning models—such as Linear Regression, Random Forest, XGBoost, and the proposed ConVLSTM architecture—are trained and evaluated. Model performance is assessed using suitable statistical metrics to determine the most effective predictive framework. Figure 2 illustrates the overall methodological workflow, encompassing data preprocessing, sequence generation, model development, and evaluation stages for AI-driven supply chain forecasting.

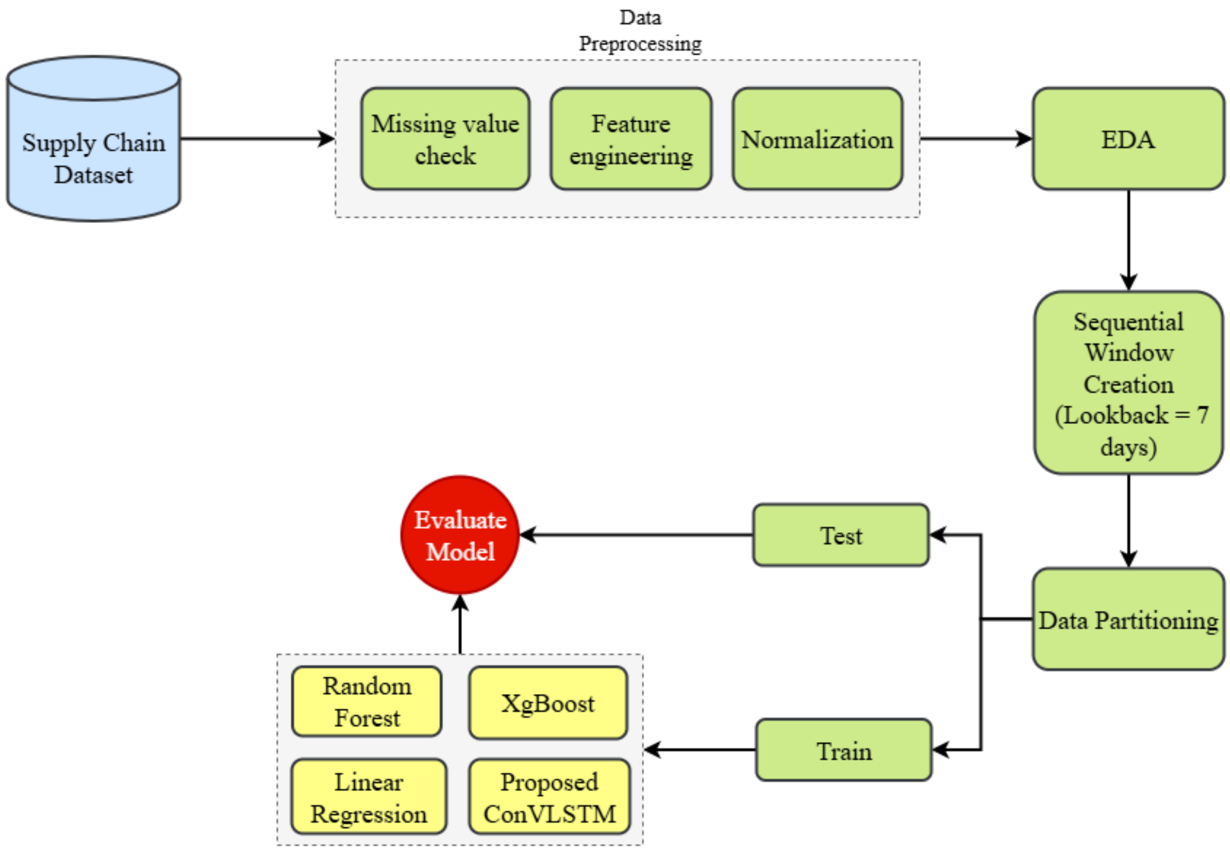

Fig. 2: Proposed methodological framework for AI-driven supply chain prediction.

Dataset:

This study utilizes the LADE (Last-Mile Delivery Dataset) developed by Wu et al. [22], which represents one of the most comprehensive industrial-scale datasets for last-mile delivery operations. For the purpose of this research, data corresponding exclusively to U.S.-based delivery records were extracted and analyzed.

Sequential Window Creation:

To prepare the data for time-series forecasting, a sequential windowing technique was applied. In this approach, the dataset was transformed into overlapping input–output pairs, where each input sequence represents the data from the previous seven days (lookback period), and the output corresponds to the next day's target value (*Total Revenue*). This sliding window method allows the model to learn temporal dependencies by observing recent historical patterns to predict future outcomes, effectively converting the continuous time-series data into a supervised learning format suitable for deep learning models such as ConvLSTM.

Convolutional Neural Network(CNN):

Convolutional Neural Networks (CNNs) are a class of deep learning models widely used in computer vision tasks such as image classification, object detection, and segmentation. They learn hierarchical representations of data through a combination of convolutional filters that extract local features, pooling layers that reduce dimensionality, and nonlinear activation functions that enhance model flexibility [23]. Although CNNs were originally developed for two-dimensional image data, their architecture can be effectively adapted for one-dimensional inputs such as time series, speech, or sensor signals [24]. In these cases, one-dimensional CNNs (Conv1D) apply filters that move along a single axis (e.g., time) to capture local temporal patterns. Stacking multiple convolutional layers enables the model to learn both short- and long-term dependencies within the data. The fundamental operation of Conv1D is the convolution, defined in Equation (1).

$$h_j = \sigma\left(\sum_{i=1}^{k} W_i . x_{j+i+1} + \mathrm{b}\right) \qquad (1)$$

x denotes the input sequence, represents the learnable weights of a kernel of size k, b is the bias term, and $\sigma(.)$ is a nonlinear activation function such as ReLU. The result, h_j is a feature value that encodes local dependencies within a window of the sequence. As the kernel slides across the input, it produces a feature map that highlights relevant sequential patterns. Once multiple convolutional and pooling layers have extracted informative features, these are flattened into a feature vector and passed through a fully connected regression layer, as expressed in Equation (2).

$$\hat{y} = W^T h + c \qquad (2)$$

Here, h denotes the learned feature representation in CNN layers, W is the vector of weights associated with the regression output layer, c is a bias term, and $\hat{y}$ is the final predicted continuous value. Figure 3 illustrates the overall architecture of a one-dimensional convolutional network, showing the flow from sequential input features through convolution and pooling layers to the final output.

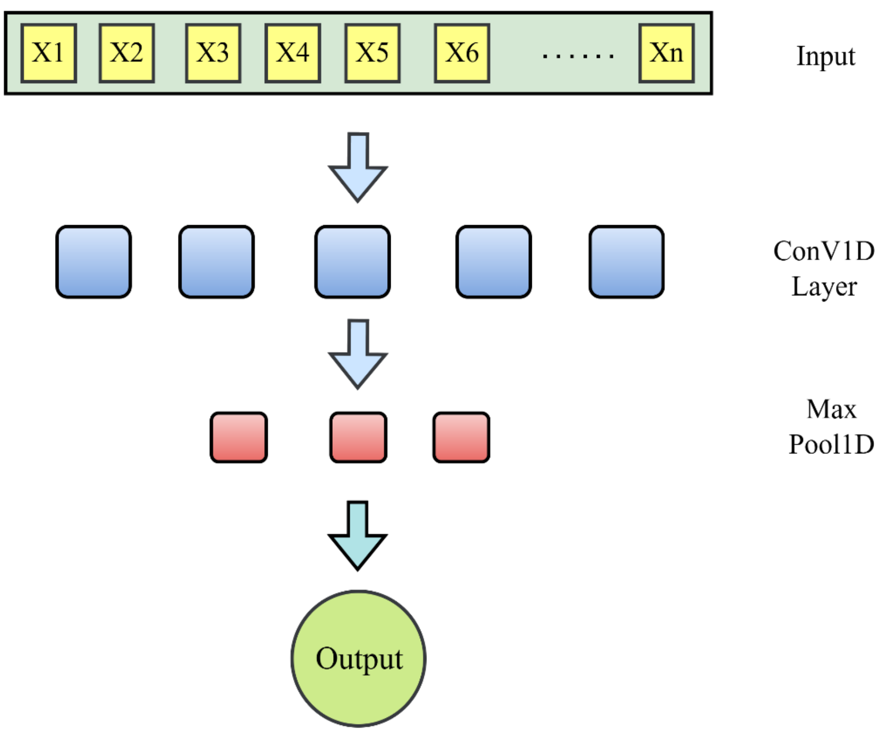

Fig. 3: Architecture of the one-dimensional Convolutional Neural Network (CNN)

Long Short Term Memory (LSTM):

Recurrent Neural Networks (RNNs) are a family of deep learning models designed to handle sequential data by maintaining a hidden state that evolves over time [25]. However, traditional RNNs often struggle with long-term dependencies due to vanishing and exploding gradient problems during training [26]. To address this limitation, Long Short-Term Memory (LSTM) networks were introduced. LSTMs augment the recurrent architecture with specialized gating mechanisms that regulate the flow of information, allowing them to retain relevant patterns over extended sequences while discarding less important details [27], [28]. An LSTM cell consists of three key gates—input gate, forget gate, and output gate—as well as a cell state that acts as a memory unit. These components enable the network to selectively update, reset, and expose information across time steps, making LSTMs particularly effective for tasks where temporal dependencies span long horizons, such as speech recognition, language modeling, physiological signal analysis, and gait prediction. The computations within an LSTM cell are summarized in Equations (3)–(8).

$$f_t = \sigma(W_i \, . [\, h_{t\ \ 1}, x_t] + b_f \ldots\ldots\ldots\ldots (3)$$

$$i_t = \sigma(W_i \, . [h_{t\ \ 1}, x_t] + b_i) \ldots\ldots\ldots\ldots\ldots (4)$$

$$\bar{C_t} = \tanh(W_c \ . [h_{t\ 1}, x_t] + b_c) \ \ldots\ldots\ldots\ldots (5)$$

$$C_t = f_t \odot C_t + i_t \odot \bar{C}_t \ldots\ldots\ldots\ldots (6)$$

$$o_t = \sigma(W_o \, . [h_{t\ 1}, x_t] + b_o \ldots\ldots\ldots\ldots\ldots (7)$$

$$h_t = o_t \tanh(C_t) \ldots\ldots\ldots\ldots\ldots (8)$$

Together, these mechanisms enable the network to regulate how much past information is retained, how much new information is added, and how much is exposed to the next layer. In this research, LSTMs were applied to model gait and biomechanical sequences, exploiting their ability to capture long-term dependencies that are not easily modeled by traditional regression approaches or shallow learners. By leveraging the gating architecture, the LSTM could learn how historical motion patterns influence future states, enabling accurate regression predictions. The internal structure of an LSTM cell, including its gating mechanisms and memory flow, is illustrated in Figure 4.

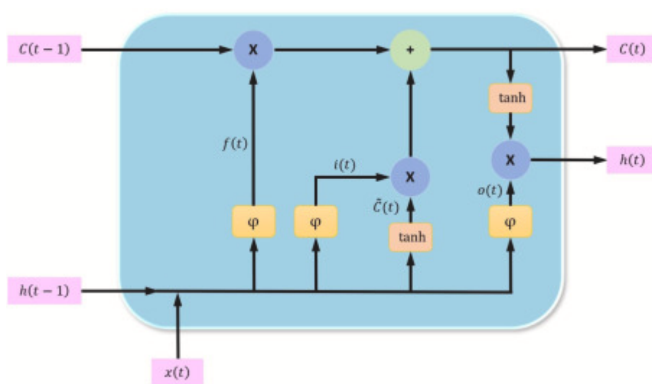

Fig. 4: Schematic representation of a Long Short-Term Memory (LSTM) cell showing the input, forget, and output gates along with the cell state and hidden state transitions [28].

Proposed ConvLSTM Model:

To effectively capture both short-term and long-term dependencies within the supply chain time series data, a hybrid Convolutional Long Short-Term Memory (ConvLSTM) model was developed. The architecture integrates the feature extraction capability of 1D Convolutional Neural Networks (Conv1D) with the sequential modeling strength of Long Short-Term Memory (LSTM) networks.

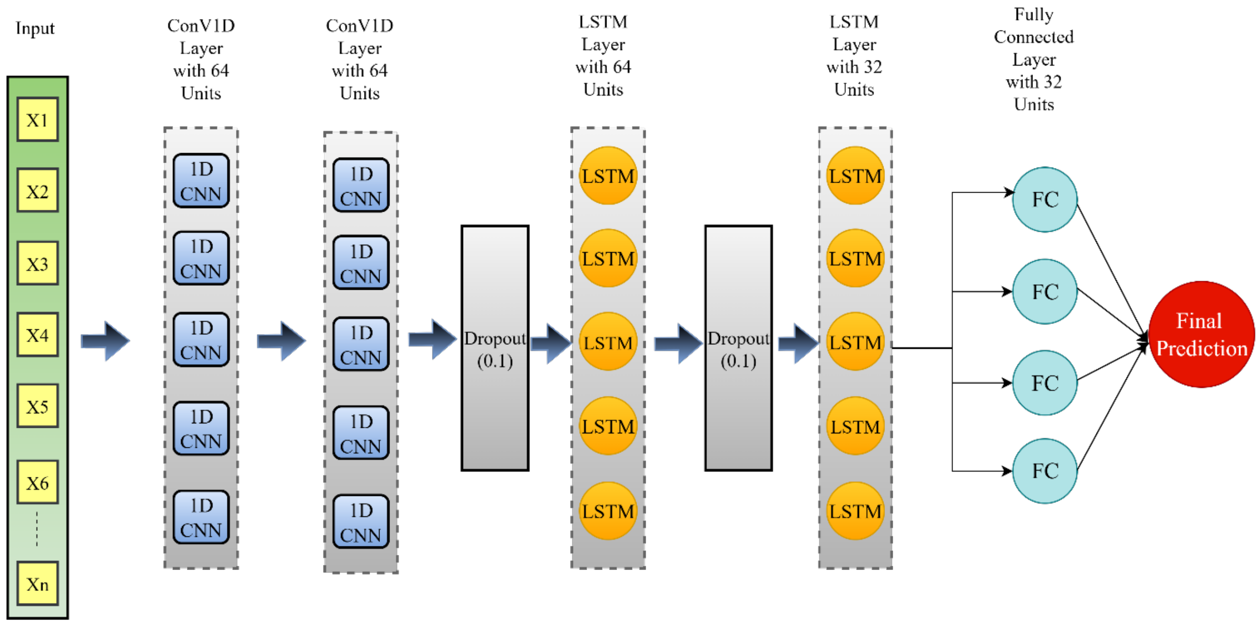

Fig. 5. Design flow of the proposed ConvLSTM-based supply chain revenue prediction model.

The model accepts input sequences of shape (time steps × features), where each time step represents the feature set for a given day within the lookback window. Initially, two Conv1D layers are employed to detect short-range temporal patterns and local correlations among the features. The use of causal padding ensures that convolutional filters respect the chronological order of data, preventing information leakage from future time steps. These layers are followed by a dropout layer to reduce overfitting and improve generalization. Next, the model incorporates two stacked LSTM layers to capture longer-term dependencies and temporal dynamics within the sequential data. The first LSTM layer returns the full sequence of outputs, enabling the second LSTM layer to learn more abstract temporal representations. A smaller number of units in the second LSTM layer promotes model regularization and computational efficiency.

Finally, the output from the LSTM layers is passed through a fully connected regression head, consisting of a dense layer with ReLU activation for nonlinear transformation, followed by a single output neuron to predict the target continuous variable — the daily total revenue. The model is optimized using the Adam optimizer with a learning rate of 0.001 and trained to minimize the Mean Squared Error (MSE) loss function, while Mean Absolute Error (MAE) is used as an evaluation metric. This hybrid ConvLSTM framework leverages CNNs for extracting localized temporal features and LSTMs for modeling sequential dependencies, making it particularly effective for complex time-series prediction tasks in dynamic supply chain environments. The summary of the proposed ConvLSTM model architecture, including layer types, output dimensions, and the number of trainable parameters, is presented in Table 1. The model comprises convolutional, recurrent, and fully connected layers, totaling 66,817 trainable parameters.

Table 1. Summary of the proposed ConvLSTM model architecture.

Layer (Type)	**Output Shape**	**Parameters**
Conv1D	(None, 7, 64)	7,936
Conv1D_1	(None, 7, 64)	12,352
Dropout	(None, 7, 64)	0
LSTM	(None, 7, 64)	33,024
Dropout_1	(None, 7, 64)	0
LSTM_1	(None, 32)	12,416
Dense	(None, 32)	1,056
Dense_1	(None, 1)	33
Total Parameters	**66,817**	**(All Trainable)**

Result Analysis:

The performance of the models on the was evaluated using three metrics: Mean Squared Error (MSE), Mean Absolute Error (MAE), and the Coefficient of Determination (R^2). These measures capture different but complementary aspects of regression performance. The Mean Squared Error (MSE) evaluates the average squared difference between the predicted and actual values (Equation 9).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad \ldots\ldots\ldots\ldots\ldots\ldots (9)$$

A lower MSE indicates better performance, with the squaring term penalizing larger errors more heavily. The Mean Absolute Error (MAE) measures the average absolute difference between predictions and actual values (Equation 10).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad \ldots\ldots\ldots\ldots\ldots\ldots (10)$$

Unlike MSE, MAE treats all errors linearly, offering a more interpretable measure of the average prediction deviation in the same units as the target variable. The Coefficient of Determination (R^2) indicates the proportion of variance in the dependent variable that is predictable from the independent variables (Equation 11).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (11)$$

Following the evaluation criteria defined in Equations (9)–(11), the performance of the proposed ConvLSTM model was assessed and compared with several baseline algorithms, including Linear Regression, Random Forest, and XGBoost. Each model was trained and evaluated under identical experimental settings to ensure the reliability and consistency of the comparative analysis. The quantitative results obtained on the test dataset are summarized in Table 2.

Table 2. Model performance comparison on test data.

Model	RMSE	MAE	R^2
Proposed ConvLSTM	**466.33**	**234.86**	**0.9880**
Linear Regression	2506.45	1423.19	0.6530
Random Forest	490.35	267.28	0.9654
XGBoost	590.35	356.28	0.9554

As illustrated in Table 2 and further visualized in Figure 7 the proposed ConvLSTM model demonstrates superior predictive capability across all three evaluation metrics. It achieves the lowest RMSE (466.33) and MAE (234.86) values and attains the highest coefficient of determination ($R^2 = 0.9880$). These results indicate that the ConvLSTM accurately captures the temporal dependencies and nonlinear relationships inherent in the supply chain time-series data, explaining approximately 98.8% of the total variance in the target variable. In contrast, the Linear Regression model exhibits the weakest performance (RMSE = 2506.45, $R^2 = 0.653$), reflecting its limited ability to model nonlinear dynamics and temporal fluctuations in sequential data.

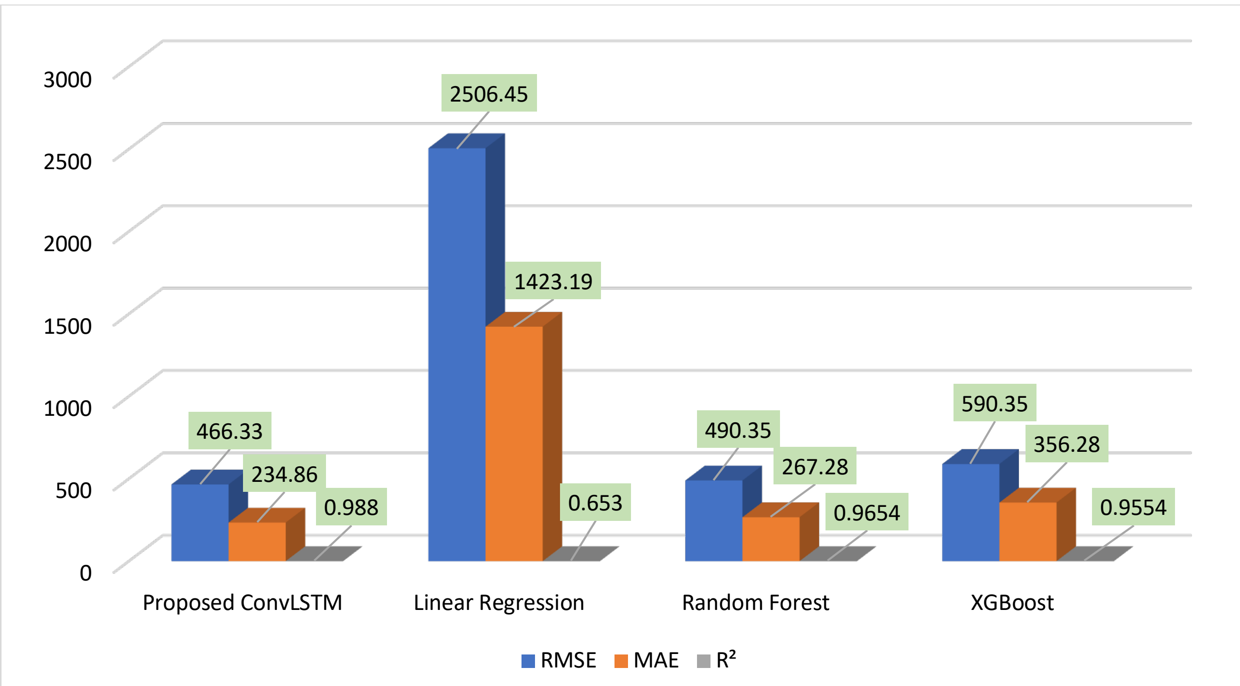

Fig. 7: Comparative performance of the proposed ConvLSTM model and baseline models based on RMSE, MAE, and R^2 metrics.

The Random Forest and XGBoost models perform considerably better, achieving R^2 values of 0.965 and 0.955, respectively. However, their prediction accuracy remains inferior to that of the ConvLSTM due to their inability to model long-term dependencies, as they treat each observation as independent and disregard the temporal structure of the input data. The proposed ConvLSTM architecture effectively integrates convolutional and recurrent learning mechanisms to address these limitations. The convolutional layers capture localized temporal features and short-term variations in the data, while the LSTM layers model longer-term dependencies and trends over time. This hybrid configuration enables the model to generalize effectively and to maintain high predictive precision even under dynamic and volatile operational conditions typical of supply chain systems.

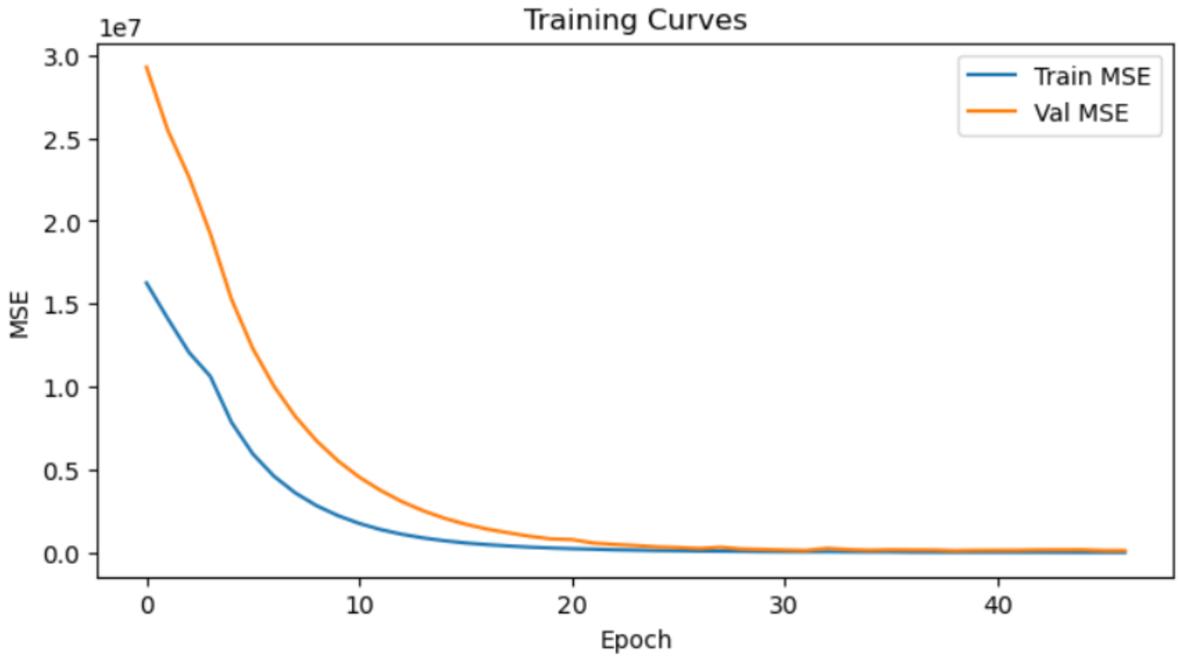

Fig. 8: Training and validation loss (MSE) curves of the proposed ConvLSTM model.

The model's training behavior is further illustrated in Figure 8, which presents the Mean Squared Error (MSE) values for both training and validation sets across epochs. The curves show a steady decline and eventual stabilization after approximately 30 epochs, indicating efficient convergence and minimal overfitting. The close alignment between the training and validation curves suggests strong generalization capability and a well-balanced learning process.

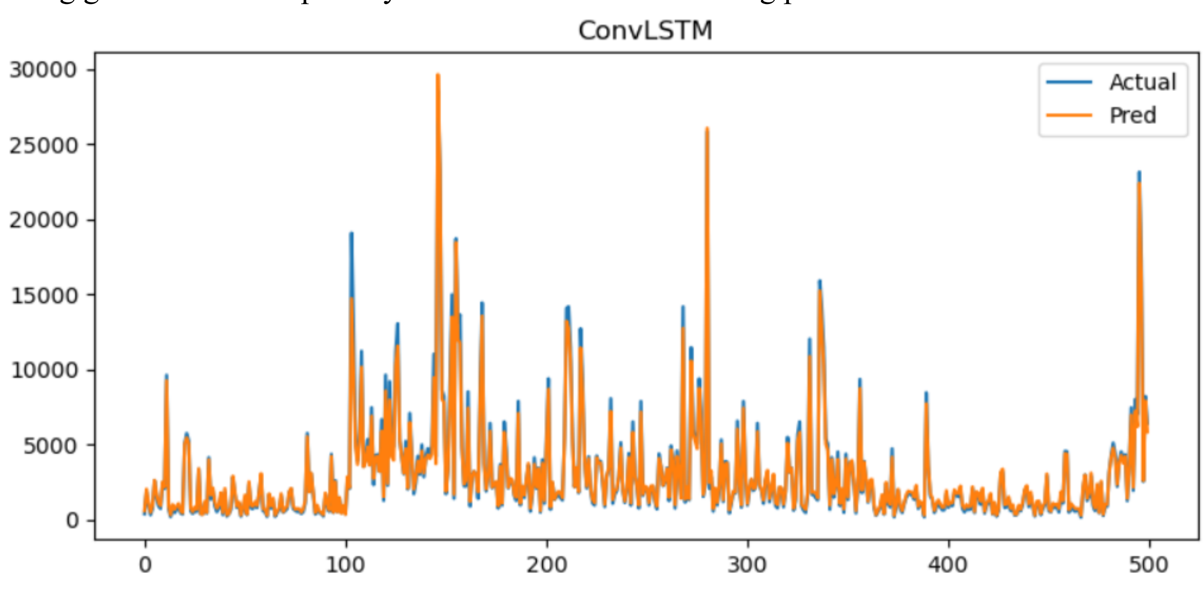

Fig. 9: Comparison of actual and predicted values for the ConvLSTM model on test data.

The predictive accuracy of the ConvLSTM is also confirmed by the visual comparison presented in Figure 9, where the predicted and actual revenue values exhibit a high degree of overlap. The model successfully captures both gradual and abrupt changes in the data, including sharp peaks and irregular variations, thereby validating its robustness in modeling real-world supply chain behavior.

In summary, the experimental findings demonstrate that the proposed ConvLSTM model substantially outperforms conventional regression and ensemble learning techniques. Its ability to jointly learn short-term local dependencies and long-term temporal relationships results in highly accurate and stable forecasts. Consequently, the ConvLSTM framework presents a promising solution for intelligent, data-driven decision-making and demand forecasting in complex supply chain environments.

Conclusion and Future Work:

The paper presented an AI-driven supply chain management predictive analytics framework, taking into account the integration of the deep learning approach to better the precision of prediction and decision-making. Based on the LADE dataset of last-mile delivery, the research developed and evaluated a number of models, including Linear Regression, Random Forest, XGBoost, and the hybrid architecture proposed by the researcher, the convoluted LSTM grouping. ConvLSTM model was found to be better predictors with a less RMSE of 466.33, MAE of 234.86, and R 2 of 0.988. These findings underscore the capability of the model to capture short-term variations as well as long-term temporal variations of the complex supply chain data. The ConvLSTM model with its hybrid architecture, a combination of the convolutional layers, where local features are extracted, and the recurrent layers, where sequence learning represents the dynamics, was especially useful in estimating the nonlinear relations and the dynamic behaviors. The comparative analysis of the offered approach with traditional and ensemble learning models proved that the proposed one is a much more reliable predictor to be used in a wide range of practical activities, including revenue prediction, demand forecasting, and operational planning. Besides the technical findings, this study supports the transformative nature of artificial intelligence in the contemporary supply chain management. The accuracy and strength portrayed by the ConvLSTM model is an indication of the possibility of deep sequential learning frameworks in facilitating data-informed decision-making and enhance supply chain responsiveness in uncertain and dynamic settings.

To work in the future, a number of directions can be offered. To begin with, multi-source data (e.g. weather conditions, economic indicators, and supplier reliability metrics) can also be added to the model so as to increase the accuracy of the forecasts. Second, attention mechanisms or transformer-based architectures could be investigated to enhance interpretability and more complicated dependencies. Lastly, the predictive framework should be included in the real-time decision-support system that would allow adaptive forecasting and dynamic optimization throughout the end-to-end processes of the supply chain. On the whole, the study adds to the existing body of knowledge on intelligent supply chain management by showing that the hybrid deep learning architecture like ConvLSTM may serve to fill the gap between the precision of analytics and the feasibility of operations to create more resilient, adaptive, and data-driven logistics networks.

References:

[1] R. Jabla, M. Khemaja, F. Buendia, and S. Faiz, "Automatic Rule Generation for Decision-Making in Context-Aware Systems Using Machine Learning," *Comput. Intell. Neurosci.*, vol. 2022, pp. 1–13, May 2022, doi: 10.1155/2022/5202537.

[2] Y. N. Liu and S. Y. Wu, "A rule-based approach for dynamic analytic hierarchy process decision-making," *Int. J. Inf. Decis. Sci.*, vol. 12, no. 1, p. 36, 2020, doi: 10.1504/IJIDS.2020.104994.

[3] A. T. Rosário and J. C. Dias, "How Industry 4.0 and Sensors Can Leverage Product Design: Opportunities and Challenges," *Sensors*, vol. 23, no. 3, p. 1165, Jan. 2023, doi: 10.3390/s23031165.

[4] X. Xu, H.-S. Kim, S.-S. You, and S.-D. Lee, "Active management strategy for supply chain system using nonlinear control synthesis," *Int. J. Dyn. Control*, vol. 10, no. 6, pp. 1981–1995, Dec. 2022, doi: 10.1007/s40435-021-00901-5.

[5] A. Aamer, L. P. Eka Yani, and I. M. Alan Priyatna, "Data Analytics in the Supply Chain Management: Review of Machine Learning Applications in Demand Forecasting," *Oper. Supply Chain Manag. Int. J.*, pp. 1–13, Dec. 2020, doi: 10.31387/oscm0440281.

[6] R. Sharma, A. Shishodia, A. Gunasekaran, H. Min, and Z. H. Munim, "The role of artificial intelligence in supply chain management: mapping the territory," *Int. J. Prod. Res.*, vol. 60, no. 24, pp. 7527–7550, Dec. 2022, doi: 10.1080/00207543.2022.2029611.

[7] M. Shrivastav, "Barriers Related to AI Implementation in Supply Chain Management:," *J. Glob. Inf. Manag.*, vol. 30, no. 8, pp. 1–19, Feb. 2022, doi: 10.4018/JGIM.296725.

[8] R. Toorajipour, V. Sohrabpour, A. Nazarpour, P. Oghazi, and M. Fischl, "Artificial intelligence in supply chain management: A systematic literature review," *J. Bus. Res.*, vol. 122, pp. 502–517, 2021.

[9] M. Pournader, A. Kach, and S. Talluri, "A review of the existing and emerging topics in the supply chain risk management literature," *Decis. Sci.*, vol. 51, no. 4, pp. 867–919, 2020.

[10] M. A. Mediavilla, F. Dietrich, and D. Palm, "Review and analysis of artificial intelligence methods for demand forecasting in supply chain management," *Procedia CIRP*, vol. 107, pp. 1126–1131, 2022.

[11] K. Douaioui, R. Oucheikh, O. Benmoussa, and C. Mabrouki, "Machine Learning and Deep Learning Models for Demand Forecasting in Supply Chain Management: A Critical Review.," *Appl. Syst. Innov. ASI*, vol. 7, no. 5, 2024.

[12] K. Tsolaki, T. Vafeiadis, A. Nizamis, D. Ioannidis, and D. Tzovaras, "Utilizing machine learning on freight transportation and logistics applications: A review," *ICT Express*, vol. 9, no. 3, pp. 284–295, 2023.

[13] F. Sunmola and G. Baryannis, "Artificial Intelligence Opportunities for Resilient Supply Chains," *IFAC-Pap.*, vol. 58, no. 19, pp. 813–818, 2024.

[14] J. Gijsbrechts, R. N. Boute, J. A. Van Mieghem, and D. J. Zhang, "Can deep reinforcement learning improve inventory management? Performance on lost sales, dual-sourcing, and multi-echelon problems," *Manuf. Serv. Oper. Manag.*, vol. 24, no. 3, pp. 1349–1368, 2022.

[15] W. Villegas-Ch, A. M. Navarro, and S. Sanchez-Viteri, "Optimization of inventory management through computer vision and machine learning technologies," *Intell. Syst. Appl.*, vol. 24, p. 200438, 2024.

[16] M. A. Mediavilla, F. Dietrich, and D. Palm, "Review and analysis of artificial intelligence methods for demand forecasting in supply chain management," *Procedia CIRP*, vol. 107, pp. 1126–1131, 2022.

[17] K. Douaioui, R. Oucheikh, O. Benmoussa, and C. Mabrouki, "Machine Learning and Deep Learning Models for Demand Forecasting in Supply Chain Management: A Critical Review.," *Appl. Syst. Innov. ASI*, vol. 7, no. 5, 2024.

[18] K. Tsolaki, T. Vafeiadis, A. Nizamis, D. Ioannidis, and D. Tzovaras, "Utilizing machine learning on freight transportation and logistics applications: A review," *ICT Express*, vol. 9, no. 3, pp. 284–295, 2023.

[19] J. Gijsbrechts, R. N. Boute, J. A. Van Mieghem, and D. J. Zhang, "Can deep reinforcement learning improve inventory management? Performance on lost sales, dual-sourcing, and multi-echelon problems," *Manuf. Serv. Oper. Manag.*, vol. 24, no. 3, pp. 1349–1368, 2022.

[20] M. A. Mediavilla, F. Dietrich, and D. Palm, "Review and analysis of artificial intelligence methods for demand forecasting in supply chain management," *Procedia CIRP*, vol. 107, pp. 1126–1131, 2022.

[21] K. Douaioui, R. Oucheikh, O. Benmoussa, and C. Mabrouki, "Machine Learning and Deep Learning Models for Demand Forecasting in Supply Chain Management: A Critical Review.," *Appl. Syst. Innov. ASI*, vol. 7, no. 5, 2024.

[22] L. Wu *et al.*, "Lade: The first comprehensive last-mile delivery dataset from industry," *ArXiv Prepr. ArXiv230610675*, 2023.

[23] A. Derry, M. Krzywinski, and N. Altman, "Convolutional neural networks," 2023.

[24] T. Hayat, M. S. Islam, M. Hossain, N. Hasan, M. Parvez, and Md. J. Hoque, "Machine Learning Techniques for Brain Tumor Classification: A CNN-SVM Approach," in *2024 International Conference on Innovations in Science, Engineering and Technology (ICISET)*, Chittagong, Bangladesh: IEEE, Oct. 2024, pp. 1–6. doi: 10.1109/ICISET62123.2024.10939981.

[25] Z. C. Lipton, J. Berkowitz, and C. Elkan, "A Critical Review of Recurrent Neural Networks for Sequence Learning," Oct. 17, 2015, *arXiv*: arXiv:1506.00019. doi: 10.48550/arXiv.1506.00019.

[26] K. Smagulova and A. P. James, "A survey on LSTM memristive neural network architectures and applications," *Eur. Phys. J. Spec. Top.*, vol. 228, no. 10, pp. 2313–2324, Oct. 2019, doi: 10.1140/epjst/e2019-900046-x.

[27] T. Fischer and C. Krauss, "Deep learning with long short-term memory networks for financial market predictions," *Eur. J. Oper. Res.*, vol. 270, no. 2, pp. 654–669, Oct. 2018, doi: 10.1016/j.ejor.2017.11.054.

[28] E. Terzi, F. Bonassi, M. Farina, and R. Scattolini, "Learning model predictive control with long short-term memory networks," *Int. J. Robust Nonlinear Control*, vol. 31, no. 18, pp. 8877–8896, Dec. 2021, doi: 10.1002/rnc.5519.