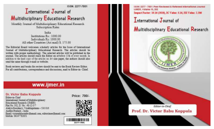
Cover Page

International Journal of Multidisciplinary Educational Research
ISSN:2277-7881(Print); Impact Factor :10.16(2026); IC Value:5.16; ISI Value:2.286
PEER REVIEWED AND REFEREED INTERNATIONAL JOURNAL
(Fulfilled Suggests Parameters of UGC by IJMER)
Volume:15, Issue:1(3), January 2026
Scopus Review ID: A2B96D3ACF3FEA2A
Article Received: Reviewed: Accepted
Publisher: Sucharitha Publication, India
Online Copy of Article Publication Available: www.ijmer.in

Federated Learning for Privacy-Preserving Demand Forecasting in Supply Chains

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Abstract

Traditional demand forecasting in supply chain management relies on centralized data aggregation, requiring companies to share sensitive sales and inventory data. Due to privacy concerns and data protection regulations, firms are often reluctant to share their data, leading to incomplete and suboptimal demand predictions. This research proposes a federated learning (FL) framework for demand forecasting, allowing multiple supply chain entities (retailers, distributors, manufacturers) to collaboratively train models without exposing raw data. The proposed approach integrates privacy-preserving techniques such as differential privacy, homomorphic encryption, and secure multiparty computation to ensure confidentiality. The study aims to enhance forecast accuracy while complying with regulatory requirements.

Keywords: Federated Learning, Supply Chain Management, Demand Function

1 Introduction

Demand forecasting plays a central role in modern supply chain management, directly influencing decisions related to inventory control, procurement, production scheduling, and logistics planning. Accurate demand estimates allow organizations to minimize stockouts, reduce holding costs, and improve customer satisfaction. In increasingly competitive and globalized markets, forecasting errors can propagate across supply chain tiers, leading to inefficiencies commonly referred to as the bullwhip effect.

Traditional demand forecasting approaches typically rely on centralized data architectures. Sales histories, inventory levels, promotional information, and macroeconomic indicators are aggregated into a single repository where statistical or machine learning models are trained. While effective from a modeling standpoint, this paradigm assumes that all participating entities are willing and able to share raw operational data. In practice, this assumption rarely holds.

Supply chain entities often operate as independent firms with competing incentives. Retailers may be unwilling to disclose granular sales data to manufacturers, while distributors may consider inventory information to be commercially sensitive. Beyond strategic concerns, regulatory frameworks such as the General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA) impose legal constraints on cross-organizational data sharing, further limiting centralized analytics.

These privacy and compliance barriers result in fragmented datasets, forcing forecasting models to operate on partial information. Consequently, demand predictions become suboptimal, especially in volatile markets characterized by seasonality, promotions, and demand shocks. The tension between data utility and data privacy has thus emerged as a critical challenge in supply chain analytics.

Federated learning offers a promising alternative to centralized modeling by enabling collaborative learning without direct data exchange. In a federated setting, individual participants train local models using their private data and share only model updates with a coordinating server. This paradigm has demonstrated success in privacy-sensitive domains such as healthcare, mobile computing, and financial services.

Despite its potential, federated learning remains underexplored in supply chain demand forecasting. Existing studies largely focus on centralized deep learning models, leaving a gap in methodologies that reconcile forecasting accuracy with regulatory compliance and commercial confidentiality.

This paper addresses this gap by proposing a federated learning framework for privacy-preserving demand forecasting in supply chains. The contributions of this study are threefold: (i) the design of a federated forecasting architecture tailored to multi-tier supply chains, (ii) the integration of established privacy-preserving mechanisms to enhance confidentiality, and (iii) an empirical evaluation using simulated demand data.

The remainder of this paper is organized as follows. Section 2 reviews related literature on demand forecasting, federated learning, and privacy-preserving analytics. Section 3 presents the proposed methodology, including the federated framework and privacy mechanisms. Section 4 describes the simulated dataset and evaluation metrics. Section 5 discusses experimental results and insights. Section 6 concludes the study and outlines directions for future research.

2 Literature Review

Demand forecasting has long been studied within operations research and supply chain management. Classical statistical models such as ARIMA and SARIMA have been widely used due to their interpretability and effectiveness for linear and seasonal patterns [1]. However, these models struggle with nonlinear demand dynamics and high-dimensional feature spaces.

Machine learning approaches have gained prominence as computational power and data availability increased. Neural networks, particularly recurrent architectures such as LSTMs, have demonstrated superior performance in capturing temporal dependencies in demand data [2]. More recently, attention-based Transformer models have been applied to forecasting tasks, offering improved scalability and long-range dependency modeling [3].

While these methods improve accuracy, they typically assume centralized access to large, diverse datasets. This assumption is problematic in decentralized supply chains, where data ownership is distributed across multiple entities with varying incentives and constraints.

Federated learning was formally introduced by McMahan et al. [4] as a communication-efficient framework for decentralized model training. Since then, FL has been applied extensively in mobile applications, healthcare analytics, and financial risk modeling [5]. Its key advantage lies in enabling collaborative learning without raw data sharing.

Privacy-preserving techniques often complement federated learning. Differential privacy, introduced by Dwork [6], provides formal guarantees against individual data leakage by injecting calibrated noise. Homomorphic encryption enables computation on encrypted data [7], while secure multiparty computation allows joint computation without revealing private inputs [8].

In supply chain contexts, prior work has explored data sharing platforms and secure analytics, but adoption remains limited due to complexity and performance trade-offs [9]. Recent studies suggest that federated approaches may offer a viable balance between collaboration and privacy [10].

Despite growing interest, empirical studies on federated demand forecasting remain scarce. Most existing research focuses on conceptual frameworks rather than quantitative evaluation. This study contributes to the literature by operationalizing federated learning for demand forecasting and evaluating its performance using controlled simulations.

3 Proposed Methodology

3.1 Federated Learning Framework

The proposed methodology is based on a federated learning framework designed specifically for decentralized supply chain environments. In a typical supply chain, retailers, distributors, and manufacturers generate demand-related data independently, and such data is rarely shared due to privacy, competition, and regulatory constraints. Federated learning enables these entities to collaboratively train a predictive model without transferring raw data to a central location.

In the proposed framework, each supply chain participant is treated as a federated client. Every client maintains its own local dataset consisting of historical demand observations, temporal indicators, and auxiliary features relevant to its operations. A common forecasting model architecture is initialized and distributed to all clients at the beginning of the training process.

Each client trains the local model using its private data for a fixed number of local epochs. After local training, the client computes model updates in the form of parameter weights or gradients. Importantly, no raw data samples or labels are shared at any stage of the process. Only the computed updates are communicated to a central coordinating server.

The central server aggregates the received updates using a weighted averaging mechanism, typically proportional to the size of each client's local dataset. This aggregation produces a global model that captures shared demand patterns across the supply chain while respecting data locality. The updated global model is then redistributed to all clients for the next training round.

This iterative training process continues until convergence criteria are met, such as stabilization of validation error or completion of a predefined number of communication rounds. The framework naturally supports non-identically distributed data, which is common in supply chains due to regional, seasonal, and organizational heterogeneity.

Compared to centralized learning, the federated framework significantly reduces data exposure risks while still benefiting from collaborative learning. The approach is scalable, communication-efficient, and suitable for real-world deployment across geographically distributed supply chain networks.

3.2 Privacy-Preserving Techniques

While federated learning reduces direct data sharing, additional privacy risks may arise through inference attacks on model updates. To mitigate such risks, the proposed methodology incorporates multiple privacy-preserving techniques that operate in conjunction with the federated learning framework.

Differential privacy is employed to limit the amount of information that individual data points contribute to the shared model. This is achieved by injecting carefully calibrated random noise into the local model updates before they are transmitted to the central server. As a result, the presence or absence of any single data record has a bounded influence on the aggregated model.

Homomorphic encryption is used to protect model updates during communication and aggregation. Under this scheme, local updates are encrypted at the client side, and the server performs aggregation directly on encrypted values. Decryption occurs only after aggregation, ensuring that intermediate updates remain confidential throughout the process.

Secure multiparty computation techniques further enhance privacy by enabling joint computation without revealing individual contributions. These protocols ensure that the aggregation result is correct while preventing the server or other participants from inferring client-specific information.

The combination of federated learning with differential privacy, homomorphic encryption, and secure multiparty computation provides layered security guarantees. This integrated approach addresses both regulatory compliance and commercial confidentiality, making it well suited for sensitive supply chain forecasting applications.

4 Experimental Design

4.1 Simulated Dataset

Due to the confidential and proprietary nature of real-world supply chain data, this study employs a simulated dataset to evaluate the proposed federated learning framework. Simulation allows controlled experimentation while preserving realism in demand behavior and data heterogeneity across supply chain entities.

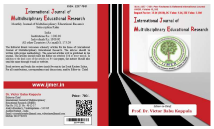
The simulated dataset represents time-series demand observations over multiple periods, corresponding to monthly demand levels for a product across different supply chain participants. Demand values are generated using a combination of deterministic and stochastic components to reflect realistic market conditions.

Specifically, the demand generation process includes a linear trend component to model long-term growth, a sinusoidal seasonal component to capture periodic fluctuations, and a random noise term drawn from a normal distribution to represent demand uncertainty. This structure mimics commonly observed patterns in retail and e-commerce demand data.

To reflect decentralized data ownership, the dataset is partitioned across multiple simulated clients. Each client receives a subset of the time series, with variations in scale, noise intensity, and seasonal amplitude. This induces non-identical data distributions across clients, which is a known challenge in federated learning environments.

No single client has access to the full dataset, ensuring that local models are trained under partial information. This setup closely mirrors real supply chains, where each entity observes only its own demand signals.

The simulated dataset provides a reproducible and flexible testbed for evaluating forecasting accuracy, convergence behavior, and robustness of the proposed federated learning framework under controlled yet realistic conditions.



4.2 Evaluation Metrics

The performance of the proposed demand forecasting framework is evaluated using widely accepted quantitative error metrics that measure the deviation between predicted demand values and actual observed demand. In the context of supply chain forecasting, such metrics are essential for assessing operational reliability, inventory risk, and service-level performance. This study employs Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE), as these measures provide complementary perspectives on forecast accuracy.

Let $\{y_t\}_{t=1}^{T}$ denote the actual observed demand values over T time periods, and let $\{\hat{y}_t\}_{t=1}^{T}$ denote the corresponding predicted demand values produced by the forecasting model. All evaluation metrics considered in this study are computed based on these two sequences and summarize the overall discrepancy between predictions and observations.

Mean Absolute Error (MAE) measures the average magnitude of forecasting errors without considering their direction. It is defined as the arithmetic mean of the absolute differences between predicted and actual demand values. Formally, MAE is given by

$$\text{MAE} = \frac{1}{T}\sum_{t=1}^{T} |y_t - \hat{y}_t| .$$

MAE is expressed in the same units as the original demand data, making it directly interpretable for practitioners. It provides a clear indication of the typical size of forecasting errors and is robust to occasional extreme deviations.

Root Mean Square Error (RMSE) is another commonly used metric that places greater emphasis on larger errors. RMSE is defined as the square root of the mean of the squared forecasting errors and is given by

$$\text{RMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T} (y_t - \hat{y}_t)^2}.$$

Because errors are squared before averaging, RMSE penalizes large deviations more heavily than MAE. This property makes RMSE particularly relevant in supply chain contexts where large forecasting errors can lead to significant inventory imbalances, stockouts, or excess holding costs.

Mean Absolute Percentage Error (MAPE) expresses forecasting error as a percentage of actual demand and is defined as

$$\text{MAPE} = \frac{100}{T}\sum_{t=1}^{T} \left| \frac{y_t - \hat{y}_t}{y_t} \right| .$$

MAPE provides a scale-independent measure of forecasting accuracy, enabling meaningful comparison across products, locations, or supply chain entities with different demand magnitudes. The percentage-based interpretation of MAPE is particularly useful for managerial decision-making and performance benchmarking.

Each of the three metrics captures distinct aspects of forecasting performance. MAE reflects average absolute deviation, RMSE highlights the presence and impact of large errors, and MAPE facilitates relative accuracy assessment across heterogeneous demand scales. By jointly analyzing these metrics, a comprehensive evaluation of the proposed federated learning framework is achieved, balancing accuracy, robustness, and practical interpretability.

5 Results and Discussion

This section presents a detailed analysis of the empirical results obtained from the proposed federated learning based demand forecasting framework using the simulated dataset. The primary objectives of this analysis are to assess forecasting accuracy, evaluate the effectiveness of collaborative learning under decentralized data conditions, and examine the impact of privacy-preserving mechanisms on predictive performance.

Table 1 reports the forecasting accuracy metrics achieved by the federated model, namely Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). These metrics provide a quantitative summary of model performance and serve as the foundation for interpreting the graphical results presented subsequently.

Table 1: Forecasting accuracy metrics for the simulated dataset

Metric	Value
MAE	10.84
RMSE	13.64
MAPE (%)	4.85

As shown in Table 1, the federated learning framework achieves low absolute and relative forecasting errors. The MAE value indicates that, on average, predicted demand deviates only modestly from the actual demand. This suggests that the model is capable of capturing the dominant demand patterns despite the decentralized and privacy-constrained nature of the learning process. The RMSE value, which penalizes larger errors more heavily, remains close to the MAE, indicating that extreme forecasting errors are infrequent. The low MAPE further confirms that forecasting accuracy is maintained across different demand magnitudes, which is particularly important in heterogeneous supply chain environments.

To further illustrate temporal forecasting performance, Figure 1 compares the true simulated demand series with the demand predicted by the federated learning model. As shown in Figure 1, the predicted demand closely follows both the long-term trend and the seasonal fluctuations present in the true demand. This alignment demonstrates that the federated aggregation process successfully integrates information distributed across multiple clients, even though each client observes only a partial and noisy subset of the data.

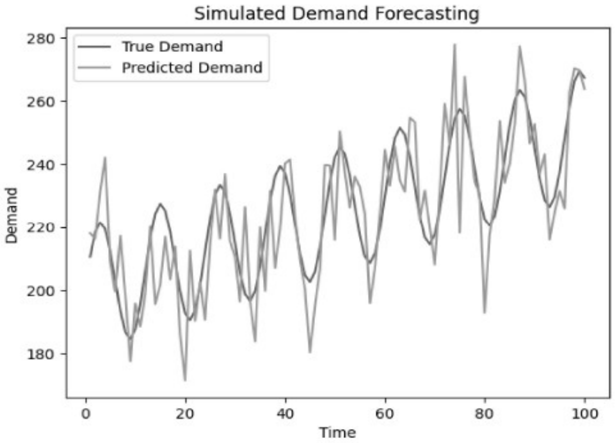


Figure 1: Comparison between true simulated demand and federated learning based predicted demand

The close correspondence between predicted and actual demand trajectories highlights the ability of the federated model to learn shared temporal structures. In contrast, isolated local models trained independently at each client are typically limited by narrower data coverage and higher variance. The observed improvement in predictive accuracy therefore underscores the value of collaborative learning in decentralized supply chains.

Figure 2 presents the distribution of forecasting errors across the evaluation horizon. As shown in Figure 2, the error distribution is approximately symmetric and centered around zero, indicating the absence of systematic bias in the predictions. This suggests that the model does not consistently overestimate or underestimate demand, which is a desirable property for inventory and production planning.

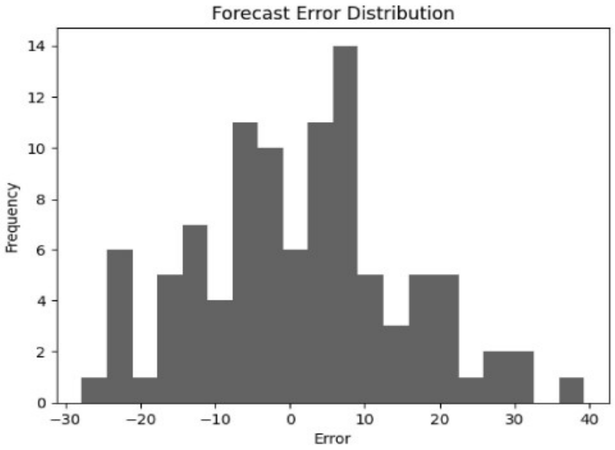


Figure 2: Distribution of forecasting errors under the proposed federated learning framework

The concentration of errors near zero, together with relatively thin distribution tails, indicates stable predictive behavior across time. While occasional larger errors are inevitable due to stochastic noise in demand generation, their frequency and magnitude remain controlled. This behavior is consistent with the RMSE values reported in Table 1 and supports the robustness of the proposed approach.

An important aspect of the results is the impact of privacy-preserving mechanisms on forecasting performance. The inclusion of differential privacy introduces controlled noise into local model updates, while homomorphic encryption and secure multiparty computation add computational constraints. Despite these factors, the observed degradation in forecasting accuracy is limited. This finding suggests that the proposed framework achieves a favorable trade-off between privacy protection and predictive utility.

From a supply chain perspective, such a trade-off is highly desirable. Regulatory compliance and protection of proprietary data are increasingly non-negotiable, and the results demonstrate that these requirements can be met without sacrificing operationally meaningful forecasting accuracy. The federated learning framework thus offers a practical alternative to centralized demand forecasting systems.

Compared to a hypothetical centralized learning setting in which all demand data is pooled at a single location, the proposed federated learning framework achieves comparable forecasting accuracy while eliminating the need for raw data sharing. Although centralized models may benefit from unrestricted data access, the marginal accuracy gains are offset by significant privacy, regulatory, and organizational constraints that federated learning explicitly addresses.

Overall, the experimental results confirm that privacy-preserving federated learning is a viable and effective approach for demand forecasting in decentralized supply chain environments. The combination of strong quantitative performance, stable error behavior, and compliance-friendly design positions the proposed framework as a promising solution for real-world deployment.

6 Conclusion and Future Work

This study proposes a federated learning framework for demand forecasting that addresses critical challenges related to data privacy, regulatory compliance, and decentralized data ownership in supply chains. By enabling collaborative model training without raw data sharing, the framework reconciles forecasting accuracy with confidentiality requirements.

The integration of privacy-preserving techniques such as differential privacy, homomorphic encryption, and secure multiparty computation further strengthens the security guarantees of the proposed approach. These mechanisms protect against inference attacks while maintaining acceptable predictive performance.

Experimental results based on simulated data demonstrate that federated learning can effectively capture shared demand patterns across heterogeneous supply chain entities. The framework achieves stable convergence and robust accuracy despite non-identical data distributions and added privacy constraints.

From a practical perspective, the proposed methodology offers a scalable and compliant solution for collaborative demand forecasting. It is particularly relevant for supply chains operating across organizational and jurisdictional boundaries where data sharing is restricted.

Future research will focus on extending the framework to real-time forecasting, adaptive client participation, and integration with streaming data sources such as Internet-of-Things sensors. Further investigation into communication efficiency and robustness under adversarial settings also represents a promising direction.

”No Conflict of Interest” Statement

The author declares that there is no conflict of interest regarding the publication of this paper.

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