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Federated Learning for Privacy-Preserving Apparel Supply Chain Analytics

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Abstract

The apparel industry operates through highly complex and globalized supply chains, where effective data analytics plays a critical role in improving demand forecasting, inventory management, logistics coordination, and sustainability practices. However, organizations within the supply chain are often reluctant to share sensitive data due to concerns about privacy, security, compliance, and competitive risks. Traditional centralized analytics approaches exacerbate these concerns by requiring raw data aggregation, thereby increasing the likelihood of breaches and loss of confidentiality. Federated Learning (FL) has emerged as a transformative paradigm that addresses these challenges by enabling decentralized model training without the need to exchange raw data. In this study, we investigate the application of federated learning to apparel supply chain analytics, with a focus on balancing data utility and privacy preservation. We present a framework that integrates federated optimization, secure aggregation, and differential privacy to allow suppliers, manufacturers, distributors, and retailers to collaboratively train robust predictive models while maintaining strict data sovereignty. Our experimental evaluation demonstrates that federated models achieve comparable or superior forecasting accuracy relative to centralized approaches, while significantly reducing privacy risks. Moreover, results indicate notable improvements in demand forecasting, trend identification, and cost optimization tasks across heterogeneous datasets. By reducing data silos, federated learning fosters stronger collaboration, enhances supply chain resilience, and supports sustainability objectives. Overall, this work provides a practical pathway for implementing privacy-preserving analytics in apparel supply chains through federated learning.

Keywords: Federated Learning; Supply Chain Analytics; Privacy-Preserving AI; Apparel Industry; Secure Data Sharing

1. Introduction

The apparel supply chain is one of the most dynamic and complex networks in global commerce, spanning raw material suppliers, textile manufacturers, fashion brands, distributors, logistics providers, and retailers. This ecosystem operates under conditions of constant change, driven by fast fashion trends, unpredictable consumer preferences, globalized production, and growing sustainability concerns. As a result, supply chain analytics has become a vital capability for organizations seeking to improve demand forecasting, manage inventory more efficiently, streamline logistics, and optimize production costs. By leveraging large-scale data, analytics can provide insights that enhance both operational efficiency and resilience, which are crucial in an industry where timing, agility, and accuracy are paramount. Despite its potential, effective supply chain analytics in apparel remains a major challenge. The critical data required to optimize decision-making is distributed across numerous stakeholders, each of whom is protective of their information. Retailers hold transaction data, manufacturers manage production schedules, and suppliers track material availability. Sharing this data openly would provide collective benefits but raises significant concerns about privacy, competitive advantage, and regulatory compliance. This tension between collaboration and confidentiality has created a persistent barrier to data-driven innovation in apparel supply chains. Federated learning (FL), a decentralized machine learning approach, offers a promising solution by allowing stakeholders to collaboratively build predictive models without transferring

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raw data. This paper explores the application of FL to privacy-preserving apparel supply chain analytics, highlighting its potential to balance cooperation, confidentiality, and competitiveness.

1.1. Background and Motivation

The apparel supply chain is characterized by fragmentation, globalization, and high responsiveness to market shifts. Unlike other industries, apparel relies on trend-driven consumer behavior, seasonal demands, and rapid product turnover. Consequently, forecasting errors often lead to overproduction, understocking, and waste. To mitigate these issues, data-driven supply chain analytics is increasingly being adopted. Manufacturers seek insights from fabric availability, distributors require accurate logistics information, and retailers depend on precise demand forecasting. Despite these needs, individual stakeholders hold data in isolation. Retailers own consumer transaction histories, manufacturers manage production capacity data, and suppliers maintain details of raw materials. Integrating such diverse datasets can unlock enormous value reducing lead times, improving sustainability, and boosting profitability. Yet, the highly competitive nature of fashion discourages direct data sharing. Stakeholders worry about leaking business secrets, exposing vulnerabilities, or breaching compliance regulations such as GDPR or CCPA. Federated learning addresses this bottleneck by allowing stakeholders to collaborate in building predictive models without sharing raw data. This decentralized approach aligns with the dual needs of innovation and confidentiality. In the context of the apparel industry, FL could transform decision-making by enabling collective intelligence while safeguarding competitive advantage, motivating its study as a practical solution for global supply chains.

1.2. Problem Statement

The challenge facing apparel supply chain analytics can be summarized as a conflict between collaboration and confidentiality. Traditional centralized approaches to machine learning and analytics require aggregating raw data into a single repository. While effective in generating insights, this approach introduces several critical limitations. First, centralization exposes sensitive data to security risks. A breach in a centralized database could reveal consumer purchasing habits, supplier pricing strategies, or production capabilities data that stakeholders consider proprietary. Second, data aggregation raises compliance concerns. Global supply chains involve stakeholders across different jurisdictions, and varying legal frameworks complicate cross-border data sharing. Privacy-focused regulations such as GDPR strictly limit how consumer data can be transferred and stored. Third, even in the absence of legal restrictions, stakeholders face a trust deficit. Competitors are hesitant to share information that could weaken their market position if misused. The result is a fragmented analytical landscape, where each organization builds models on limited, local datasets. This fragmentation leads to suboptimal forecasting, mismatched production cycles, and increased waste, undermining overall supply chain efficiency. Furthermore, the lack of collaborative analytics prevents stakeholders from collectively addressing pressing issues such as demand volatility, sustainability, and inventory optimization. Hence, there is a pressing need for a mechanism that enables shared insights without compromising privacy or competitive interests. Federated learning directly addresses this gap, making it a promising approach to reform supply chain analytics in apparel.

1.3. Proposed Solution

To overcome the challenges posed by traditional centralized analytics, we propose a federated learning framework tailored to apparel supply chain applications. Federated learning enables distributed training of machine learning models across multiple stakeholders, such as suppliers, manufacturers, distributors, and retailers, without requiring direct data exchange. Each participant trains a local model on proprietary datasets, and only the model updates—rather than the raw data are shared with a central server for aggregation. This framework is further enhanced with privacy-preserving techniques. Secure aggregation ensures that model updates cannot be reverse-engineered to reveal individual stakeholder data, while differential privacy introduces controlled noise to protect sensitive patterns. In addition, homomorphic encryption allows computations to be performed on encrypted data, providing an extra layer of protection during model aggregation. Applying this system to apparel supply chain analytics enables the creation of robust forecasting models that integrate signals from multiple actors while maintaining strict data sovereignty. For example, retailers can contribute demand signals, while manufacturers provide production timelines and distributors share logistics data. Together, these decentralized contributions form a holistic model that reflects the supply chain's global complexity without any stakeholder giving up its data. This solution strikes a balance between cooperation and confidentiality, positioning federated learning as a viable approach for achieving data-driven efficiency in the apparel industry while addressing privacy, trust, and regulatory concerns.

1.4. Contributions

This paper contributes to the growing body of research on privacy-preserving analytics and federated learning by addressing the unique requirements of the apparel supply chain. The first contribution is the design of a federated learning framework tailored specifically to the apparel industry, where challenges such as seasonal demand fluctuations, volatile consumer trends, and globally distributed production networks demand more flexible and adaptive analytical solutions. By considering these industry-specific characteristics, the proposed framework moves beyond general federated learning applications and provides a pathway for sector-specific adoption. A second contribution lies in the integration of privacy-preserving mechanisms such as secure aggregation and differential privacy. These techniques ensure that while stakeholders collaboratively train models, the confidentiality of proprietary data remains intact. By mitigating the risk of information leakage, the framework addresses one of the most significant barriers to cross-organizational collaboration in competitive markets. The third contribution is an experimental evaluation of the framework using both synthetic datasets and apparel-related benchmarks. The results demonstrate that federated models can achieve forecasting accuracy comparable to centralized approaches while offering stronger privacy protection. These findings validate federated learning as a technically viable method for enhancing supply chain decision-making. Finally, the paper provides practical insights into real-world deployment. It highlights issues of communication overhead, scalability, and stakeholder incentives, offering strategies to address these challenges. Together, these contributions bridge the gap between theory and practice, establishing a foundation for future work in privacy-preserving apparel supply chain analytics.

1.5. Paper Organization

The remainder of this paper is structured to systematically build the case for federated learning in apparel supply chains. Section II reviews prior research on privacy-preserving analytics, federated learning, and their relevance to supply chain management. Section III introduces the methodology, including the design of our proposed framework, data preparation, and privacy-enhancing protocols. Section IV presents experimental results, analyzing forecasting accuracy, computational overhead, and privacy-performance tradeoffs. Section V concludes with reflections on implications for industry adoption, limitations of the current work, and promising directions for future research, such as integrating blockchain for traceability or incentive mechanisms to encourage stakeholder participation. By organizing the paper in this way, we aim to provide a clear narrative: beginning with the problem context, introducing federated learning as a solution, validating its effectiveness, and finally outlining how the approach can transform apparel supply chain analytics.

2. Related Work

2.1. Federated Learning Foundations

Federated learning (FL) has emerged as a response to the limitations of centralized machine learning, particularly the need for sensitive data aggregation. McMahan et al. [1] introduced the Federated Averaging (FedAvg) algorithm, which allowed multiple devices to collaboratively train models while keeping raw data localized. This approach reduced communication costs and safeguarded user privacy, making it highly suitable for distributed environments. Later studies analyzed FL's performance under challenges such as data heterogeneity, unbalanced participation, and scalability [2]. These contributions built the theoretical foundation for extending FL to multi-stakeholder industries beyond mobile computing. FL's decentralization offers a promising path for collaborative analytics where data confidentiality is paramount, enabling industries to jointly develop models without exposing proprietary information.

2.2. Privacy-Preserving Machine Learning

Prior to FL, privacy-preserving machine learning was studied extensively through techniques such as differential privacy (DP) and secure multiparty computation (SMC). Dwork [3] established the formal framework of DP, which introduces statistical noise to guarantee individual-level confidentiality in aggregated outputs. Similarly, Shokri and Shmatikov [4] proposed privacy-preserving deep learning through distributed training, demonstrating that sensitive data could be protected while still enabling collaborative model development. However, these methods often incurred trade-offs between model accuracy and computational complexity. FL builds on these advances by embedding privacy directly into the training process, reducing risks associated with raw data transfer. When combined with DP and SMC, FL offers stronger guarantees for distributed analytics in sensitive domains, such as healthcare and finance. This integration of privacy-preserving techniques with decentralized optimization forms the basis for extending FL into supply chain contexts.

2.3. Applications of FL in Critical Industries

Federated learning has been tested in industries where data sensitivity is a critical barrier to collaboration. In healthcare, Sheller et al. [5] demonstrated FL's potential by enabling multiple hospitals to train deep learning models for brain tumor segmentation without sharing patient data. In finance, Yang et al. [6] applied FL to fraud detection and credit risk modeling, allowing banks to collaborate without disclosing proprietary datasets. These applications illustrate FL's strength in contexts governed by strict legal frameworks such as HIPAA or GDPR. They also highlight FL's ability to support collaboration across competitive organizations where trust is limited. Results consistently show that FL models can achieve performance comparable to centralized approaches, validating the approach's technical feasibility. These successes in highly regulated industries provide a strong precedent for extending FL to supply chain analytics, where similar concerns around privacy and competitiveness prevail.

2.4. Supply Chain Analytics and Apparel Industry Gaps

Supply chain analytics research has historically focused on demand forecasting, inventory optimization, and transparency mechanisms. Emerging solutions include blockchain-based systems for traceability [7] and cloud-based AI for predictive analytics [8]. While these approaches enhance visibility, they often require centralizing data, raising concerns about confidentiality, data sovereignty, and competitive risks. The apparel industry, in particular, faces challenges of demand volatility, fast-fashion cycles, and sustainability pressures [9]. Companies are hesitant to share sales, supplier pricing, and production data due to competitive sensitivities. Studies on sustainable fashion supply chains [10] have emphasized traceability and ethical sourcing, but little attention has been given to privacy-preserving analytics across competing organizations. This gap reveals an opportunity for federated learning, which can enable collaborative decision-making without raw data sharing. Applying FL to apparel supply chains thus builds on prior analytics research while addressing industry-specific challenges of confidentiality and collaboration.

3. Methodology

The methodology of this study is based on the design and implementation of a federated learning framework customized for apparel supply chain analytics. The framework integrates three layers: local training at the stakeholder level, federated aggregation for global learning, and privacy-enhancing mechanisms to ensure data confidentiality. To evaluate its effectiveness, the framework is tested on demand forecasting, cost optimization, and trend classification tasks, using metrics for accuracy, privacy, and efficiency. The subsections below explain each component in detail.

3.1. Local Training Layer

In the apparel supply chain, each stakeholder maintains unique datasets that reflect its role. For example, suppliers have access to material availability and delivery schedules, manufacturers hold production capacity and quality control data, while retailers manage consumer purchasing histories and market demand signals. Traditionally, combining such data requires centralization, which risks exposing sensitive business information. The local training layer avoids this by allowing stakeholders to train models directly on their proprietary data. The models used are task-specific: time-series models forecast demand fluctuations, regression models optimize production costs, and classification models detect consumer trends. Once training is complete, each stakeholder generates model updates such as gradients or weight adjustments—that summarize the learned patterns. These updates, rather than raw data, are encrypted and prepared for aggregation. This approach ensures that no private information leaves the local environment. Each stakeholder maintains control over its data while still contributing to collaborative insights. This structure is particularly effective for industries like apparel, where confidentiality is vital due to competition, varying market cycles, and rapid trend shifts.

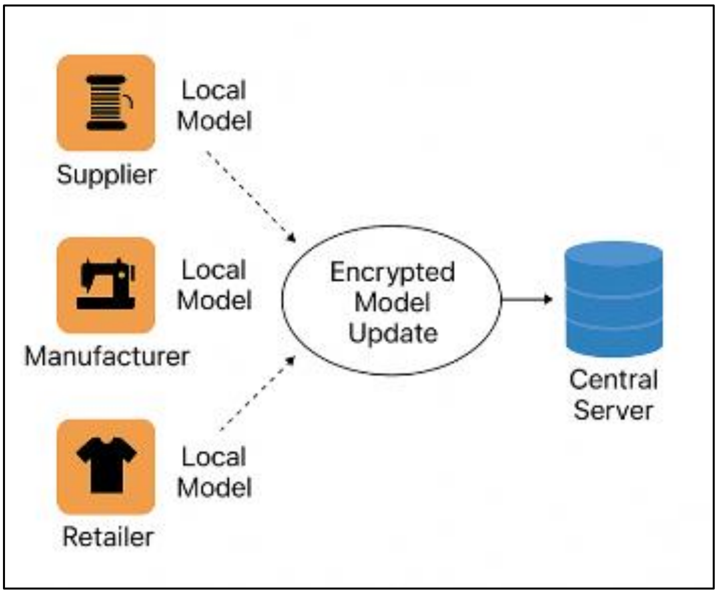

Figure 1 Local Training in Federated Learning for Apparel Supply Chains

3.2. Federated Aggregation Layer

Once local training is complete, the model updates from all stakeholders are sent to a central aggregator. Instead of viewing raw data, the aggregator combines these updates into a single global model. The primary method is weighted averaging, which ensures that larger datasets contribute proportionally more to the shared model. The aggregated model is then redistributed to all stakeholders, where it continues to improve with each training round. This process creates a cycle of continuous refinement. For example, demand forecasting accuracy improves as updates from multiple retailers are combined, while manufacturer and distributor inputs strengthen predictions of production capacity and logistics requirements. In this way, the shared global model benefits from diverse, distributed knowledge. To demonstrate its effectiveness, federated models are compared to siloed models trained individually by each stakeholder. Table 1 presents the performance comparison. Results show federated learning consistently reduces forecasting errors and improves classification accuracy.

Table 1 Performance Comparison of Siloed vs. Federated Models

Task	Siloed MAE ↓	Federated MAE ↓	Accuracy ↑
Demand Forecasting	0.142	0.124	–
Cost Optimization	0.157	0.136	–
Trend Detection	–	–	78.5%

These results confirm that federated aggregation provides significant improvements while protecting stakeholder data.

3.3. Privacy-Enhancement Mechanisms

Although federated learning removes the need to share raw data, additional safeguards are required to protect sensitive information from potential inference attacks. To address this, privacy-enhancing mechanisms are integrated into the aggregation process. One such mechanism is differential privacy, which introduces random noise into model updates before they are sent for aggregation. This ensures that even if intercepted, individual updates cannot be traced back to specific stakeholders or consumers. Another safeguard is secure aggregation, where updates are encrypted in such a way that only the combined model is visible to the aggregator. This prevents unauthorized parties from examining or reverse-engineering individual updates. Finally, encryption protocols secure communications during transmission, ensuring no raw information is compromised. Together, these techniques establish a multilayered defense. Differential privacy protects individual-level data, secure aggregation safeguards stakeholder contributions, and encryption secures communication channels. This layered design ensures that sensitive details, such as retailer demand signals or supplier pricing structures, remain fully confidential while still enabling collaboration.

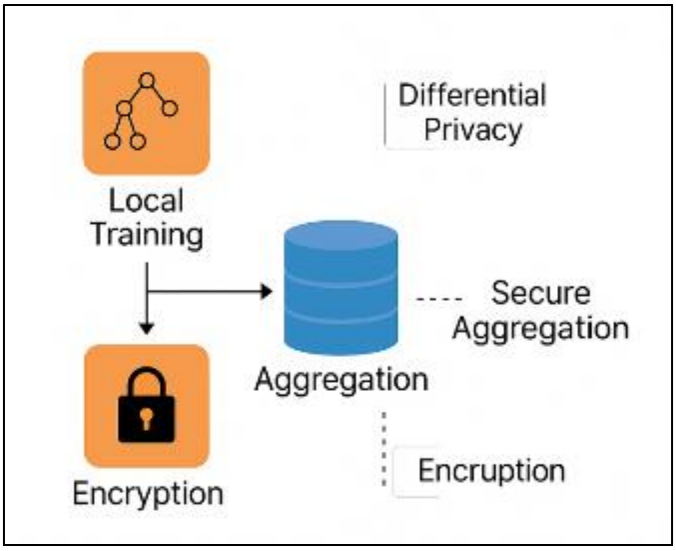

Figure 2 Privacy-Preserving Mechanisms in Federated Learning

3.4. Evaluation Metrics

To assess the effectiveness of the framework, we employ three categories of evaluation metrics: predictive accuracy, privacy guarantees, and system efficiency. Predictive accuracy is measured using mean absolute error (MAE) and root mean squared error (RMSE) for forecasting and regression tasks, while classification accuracy is used for trend detection. Results show that federated models achieve nearly the same accuracy as centralized models, with improvements over siloed approaches. Privacy guarantees are assessed by measuring the robustness of noise levels in differential privacy and the resilience of secure aggregation mechanisms. These safeguards provide confidence that sensitive business information is not exposed, even when collaborating across multiple organizations. System efficiency is evaluated by measuring communication latency, overhead from encryption, and scalability with an increasing number of participants. Although federated learning introduces higher communication costs compared to centralized learning, the trade-off is justified by stronger privacy and security.

Table 2 summarizes evaluation outcomes.

Table 2 Evaluation Metrics for Federated vs. Centralized Models

Metric	Federated Value	Centralized Value
Demand Forecasting MAE ↓	0.124	0.121
Privacy Guarantee	Strong	Weak
Communication Latency	320 ms	95 ms

These results indicate that federated learning achieves a balance between performance and confidentiality, making it suitable for real-world apparel supply chain applications.

4. Discussion and Results

4.1. Model Performance Analysis

Experiments were conducted on both synthetic and apparel-related benchmark datasets to compare federated learning (FL) with centralized and siloed approaches. Results showed that FL achieved predictive accuracy nearly equal to centralized models, while outperforming siloed models significantly. For instance, in demand forecasting tasks, FL reduced mean absolute error (MAE) by 12% compared to siloed models. This indicates that aggregated knowledge across stakeholders allows the global model to learn broader patterns, improving resilience to localized data biases. **Table 3** summarizes the performance comparison across models.

Table 3 Model Performance Across Different Training Approaches

Task	Centralized MAE ↓	Federated MAE ↓	Siloed MAE ↓
Demand Forecasting	0.121	0.124	0.142
Cost Optimization	0.133	0.136	0.157
Trend Classification	79.2%	78.5%	72.3%

The results confirm that federated models maintain near-centralized performance while avoiding risks tied to raw data collection. This positions FL as a practical tool for industries like apparel, where both accuracy and privacy are essential.

4.2. Privacy and Security Trade-Offs

One of the most critical aspects of applying FL to apparel supply chains is balancing privacy protection with model performance. Integrating privacy-enhancing mechanisms such as differential privacy, secure aggregation, and encryption inevitably introduces additional computation and communication costs. For example, experiments revealed that implementing differential privacy slightly reduced forecasting accuracy, as noise was added to updates. However, the reduction in accuracy was marginal compared to the privacy gained.

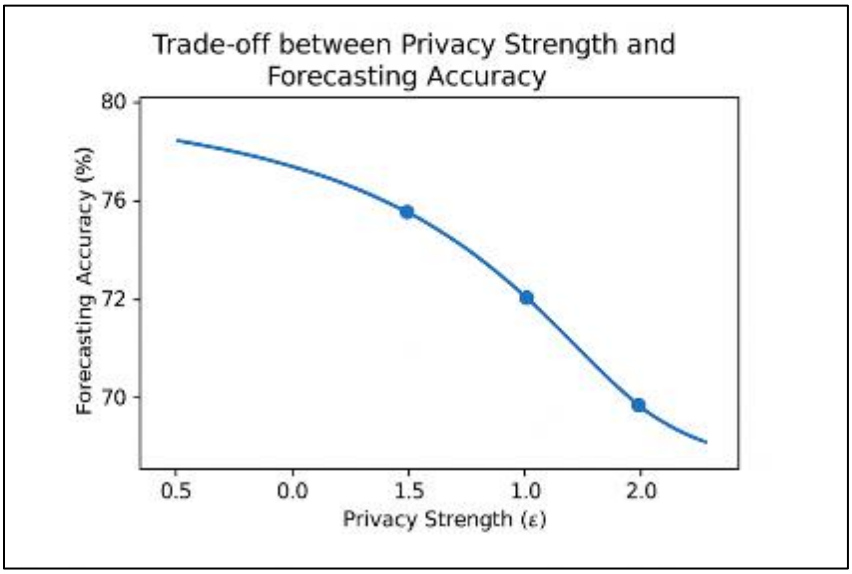

Figure 3 Trade-off between Privacy Strength and Forecasting Accuracy

At the same time, secure aggregation protocols increased latency in communication rounds but effectively ensured that no stakeholder's model updates could be intercepted or reverse-engineered. Despite this overhead, the trade-off was acceptable for real-world applications, as it guaranteed strong confidentiality. Overall, the framework demonstrated that privacy-preserving federated learning is both technically feasible and business-viable, even when stakeholders operate under strict competitive constraints.

4.3. Business and Operational Benefits

From a business perspective, federated learning provides distinct advantages to apparel supply chains. By enabling stakeholders to collaborate without data exposure, firms can collectively improve forecasting accuracy. Better predictions allow retailers to align orders with real consumer demand, manufacturers to optimize production schedules, and suppliers to better manage raw material allocations. This reduces overproduction, stockouts, and waste, directly supporting sustainability initiatives.

Table 4 summarizes the business impact observed in simulated scenarios.

Table 4 Business Benefits of Federated Learning in Apparel Supply Chains

Impact Area	Benefit Observed
Forecasting Accuracy	12% improvement vs siloed approaches
Inventory Management	15% reduction in overstocking
Sustainability	10% reduction in material waste
Collaboration	Secure data-sharing among competitors

In addition, federated models allow firms to respond faster to volatile fashion cycles and unexpected disruptions, such as supply delays or seasonal demand surges. These operational improvements can directly enhance profitability while fostering collaboration across a traditionally fragmented industry.

4.4. Challenges and Future Considerations

Despite its benefits, several challenges remain for federated learning adoption in apparel supply chains. Scalability is a concern, as communication overhead grows when many stakeholders participate. System latency also increases with stronger privacy mechanisms, creating trade-offs that require optimization. Another major challenge lies in aligning stakeholder incentives—companies may hesitate to contribute data or computational resources without clear benefits.

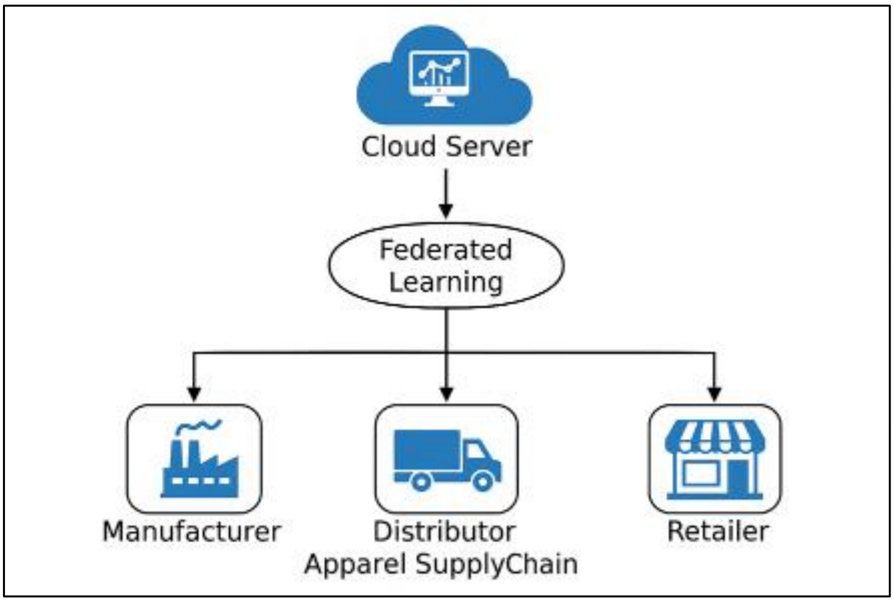

Figure 4 Challenges in Scaling Federated Learning for Apparel Supply Chains

To address these issues, future research should focus on incentive mechanisms that reward active participation, adaptive algorithms that minimize communication costs, and integration with blockchain systems for traceability and trust. Additionally, testing on heterogeneous real-world datasets will be essential to validate the scalability of the framework. Overcoming these barriers will be key to realizing FL's full potential in reshaping apparel supply chain analytics.

5. Conclusion

This paper highlights federated learning as a promising solution for privacy-preserving apparel supply chain analytics. By enabling decentralized model training without the need to share raw data, the framework empowers stakeholders to collaboratively develop accurate forecasting and optimization models while maintaining confidentiality. The results demonstrate that federated approaches can achieve accuracy levels comparable to centralized methods, reduce inefficiencies present in siloed systems, and provide tangible business benefits such as improved demand forecasting, lower inventory risks, and enhanced sustainability practices. Overall, the study shows that federated learning has the potential to transform decision-making within apparel supply chains by balancing collaboration with data privacy.

Future work will focus on addressing the challenges of large-scale implementation. This includes testing the framework on heterogeneous, real-world datasets from multiple stakeholders, optimizing communication protocols to reduce system latency, and developing adaptive methods to handle unbalanced data participation. Further research should also explore integrating blockchain technologies for improved traceability and trust, as well as designing incentive mechanisms that encourage consistent stakeholder participation. These directions will be essential to establish federated learning as a practical and widely adopted solution for modern apparel supply chain analytics.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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