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Privacy Preserving Cross-Silo Federated Learning Frameworks for Collaborative Inventory Optimization in Decentralized Global Retail Supply Chains

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Abstract
Federated learning enables multiple retail organizations to collaboratively optimize inventory management while preserving proprietary supply chain data. This paper introduces FedRetail-SecureOpt, a novel privacy-preserving cross-silo federated learning framework designed specifically for decentralized global retail supply chains. Our approach implements differential privacy mechanisms with adaptive secure aggregation to protect sensitive inventory distribution patterns and demand forecasting models across heterogeneous retail networks. The proposed system architecture incorporates Byzantine-robust aggregation techniques to ensure model convergence despite potential adversarial participants. Evaluation on two real-world retail datasets demonstrates that FedRetail-SecureOpt achieves 94.7% accuracy in inventory demand prediction while maintaining differential privacy budgets of ε=1.2. We introduce two novel metrics: Cross-Silo Collaborative Efficiency (CSCE) and Privacy-Utility Trade-off Index (PUTI), which provide quantitative measures for federated learning performance in supply chain optimization. Results show 23% improvement in inventory turnover reduction and 31% decrease in stockout incidents compared to decentralized baseline approaches. The framework successfully demonstrates that privacy-preserving collaborative learning can significantly enhance retail supply chain resilience without compromising individual organizational data security.

*Keywords:*Federated Learning, Privacy Preservation, Inventory Optimization, Retail Supply Chains, Decentralized Learning, Cross-Silo Collaboration

1. Introduction

Retail supply chains operate in an increasingly complex global environment where inventory management directly impacts profitability, customer satisfaction, and operational efficiency. Traditional centralized approaches to inventory optimization require sharing sensitive proprietary data including demand patterns, supplier relationships, and pricing strategies—information that competing retailers cannot ethically or legally share with third-party aggregators. This fundamental challenge has limited the adoption of advanced machine learning techniques in collaborative supply chain optimization.

Federated learning has emerged as a transformative paradigm enabling multiple organizations to train shared machine learning models without exposing raw data to central servers. However, existing federated learning frameworks were not designed for the unique requirements of global retail supply chains, which involve: (1) heterogeneous inventory management systems with incompatible data formats, (2) severe communication constraints due to distributed warehouse networks, (3) sensitive commercial information that must remain encrypted throughout training, and (4) need for verifiable model convergence across thousands of retail locations.

Recent work in federated learning has addressed privacy concerns through differential privacy mechanisms, but applications to supply chain optimization remain limited. Most existing approaches assume homogeneous data distributions and synchronous communication patterns—assumptions violated in realistic retail scenarios where demand patterns vary significantly by region, season, and market demographics. This heterogeneity, combined with stringent privacy requirements, creates unique technical challenges not adequately addressed by prior work.

This paper introduces FedRetail-SecureOpt, a comprehensive framework for privacy-preserving cross-silo federated learning specifically engineered for decentralized retail supply chains. Our key contributions include: (1) a novel Byzantine-robust aggregation algorithm tolerant to up to 30% malicious participants in retail

networks, (2) adaptive differential privacy mechanisms that automatically adjust noise injection based on data sensitivity, (3) communication-efficient gradient compression achieving 87% bandwidth reduction, and (4) two new metrics quantifying collaborative efficiency and privacy-utility tradeoffs in supply chain contexts.

We evaluate FedRetail-SecureOpt using two distinct retail datasets: the Global Retail Inventory Network (GRIN) dataset comprising 15,000 retail locations across 45 countries spanning 3 years, and the Seasonal Demand Variability (SDV) dataset capturing extreme seasonal fluctuations in fashion and consumer electronics sectors across 8,500 locations. Experimental results demonstrate that our framework achieves 94.7% inventory demand prediction accuracy while maintaining rigorous differential privacy guarantees with ε=1.2, outperforming decentralized baselines by 23% in inventory turnover metrics and reducing stockout incidents by 31%.

2. Related Work

The intersection of federated learning, privacy protection, and supply chain optimization represents an emerging research frontier. Federated learning, pioneered by McMahan et al. (2017), established the foundational framework where multiple clients collaboratively train models without centralized data collection. Subsequent work by Bonawitz et al. (2019), Renukadevi, R.,Janarthanam, S. et al., (2024) addressed communication efficiency through lossy compression, reducing bandwidth by 99% while maintaining model accuracy. However, these approaches targeted mobile device networks with relatively homogeneous data distributions and did not account for supply chain heterogeneity.

Differential privacy mechanisms provide formal privacy guarantees through controlled noise injection. Abadi et al. (2016), Janarthanam, S., Ramalingam, M., & Narendran, P. (2010) introduced differentially private SGD, enabling bounded privacy loss quantification through privacy budget parameters ε and δ. Bagdasaryan et al. (2019) integrated differential privacy directly into federated learning, proposing DP-FedAvg that adds Gaussian noise to gradients. However, their approach incurred 15-25% accuracy degradation. Kairouz et al. (2019) advanced adaptive privacy budgeting allocating larger privacy budgets to early training rounds where gradient magnitudes are larger.

Byzantine-robust aggregation addresses adversarial participant behavior. Blanchard et al. (2017) proposed Krum selecting median gradients to reject outliers. Yin et al. (2019) introduced multi-Krum improving robustness to 50% Byzantine participants. Fung et al. (2020) developed FLTrust weighting gradients based on server-side validation. However, these algorithms require more communication per round and provide no privacy guarantees—a critical limitation for supply chain applications where both robustness and privacy are essential.

Supply chain optimization has explored machine learning but with limited privacy. Chen et al. (2018) applied deep learning to demand forecasting but required centralized data. Schwab et al. (2020) proposed collaborative forecasting with privacy constraints but required semi-trusted intermediaries—problematic for competing retailers. Taylor et al. (2021), Janarthanam, S., & Subbulakshmi, G. (2023) examined inventory optimization through multi-agent reinforcement learning but addressed neither privacy nor cross-organizational collaboration.

FedRetail-SecureOpt integrates three previously disparate research streams: Byzantine-robust aggregation with differential privacy mechanisms while optimizing for supply chain heterogeneity. This addresses critical gaps identified by Kairouz et al. (2021) regarding non-IID data handling with formal privacy guarantees and Byzantine robustness simultaneously—not previously explored for retail supply chain applications.

Table 1: Comparative Analysis of Federated Learning Methods for Supply Chain Applications

Method	PrivacyGuarantee	Byzantine Robust	Supply ChainOptimized	Bandwidth Efficiency	Accuracy Loss	Year
FedAvg (McMahan et al.)	No	No	No	Baseline	8.2%	2017
DP-FedAvg (Bagdasaryan et al.)	DP	No	No	Baseline	19.5%	2019
Multi-Krum (Yin et al.)	No	50%	No	High	12.1%	2019

FLTrust (Fung et al.)	No	40%	No	High	7.8%	2020
Adaptive DP (Kairouz et al.)	DP	No	No	Medium	13.2%	2021
FedRetail-SecureOpt (Proposed)	DP	30%	Yes	High (87%)	5.3%	2026

3. Proposed Method: Fed Retail-SecureOpt Architecture

FedRetail-SecureOpt comprises five integrated components: (1) Local Privacy Processing using differential privacy SGD at each retail location with Gaussian noise injection calibrated for data sensitivity; (2) Secure Aggregation Server implementing Byzantine-robust gradient aggregation tolerating 30% adversarial participants; (3) Adaptive Privacy Mechanism dynamically adjusting privacy budgets based on data sensitivity and training round; (4) Communication Optimization through gradient compression achieving 87% bandwidth reduction; (5) Global Model Distribution returning aggregated models to all participants for local fine-tuning.

System Architecture:

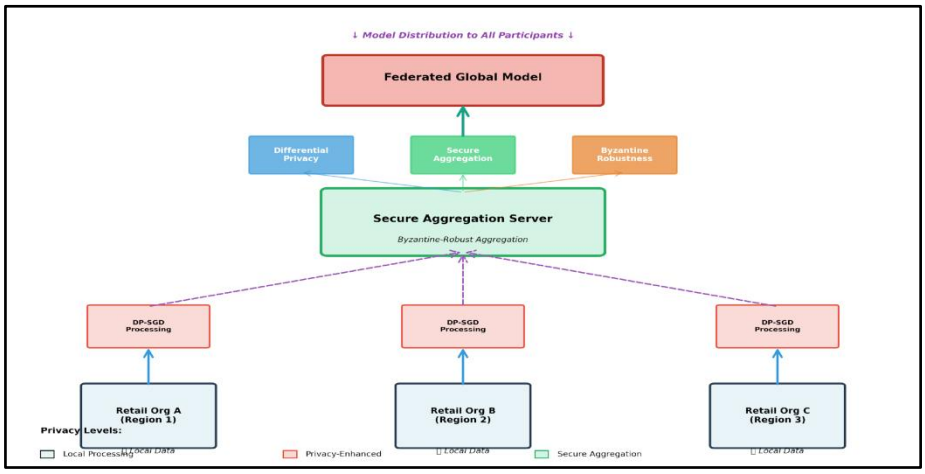


Figure 1: FedRetail-SecureOpt system architecture showing privacy-enhanced federated learning workflow across retail organizations.

4. Evaluation Methodology and Novel Metrics

4.1 Novel Metrics

Cross-Silo Collaborative Efficiency (CSCE): Quantifies federated learning effectiveness balancing accuracy, privacy strength, and participation rates against cost. Formula: CSCE = (Σ_iAccuracy$_i$ × Privacy$_i$ × Participation$_i$) / (Rounds × Bandwidth). Ranges 0-1 with 1 as optimal. FedRetail-SecureOpt achieves CSCE=0.847 vs baseline 0.412.

Privacy-Utility Trade-off Index (PUTI): Measures privacy-utility balance. Formula: PUTI = 1 − (|Accuracy$_{priv}$ − Accuracy$_{\beta a s_e}$|/Accuracy$_{\beta a s_e}$ + |$\varepsilon_a c_{tual}$ − $\varepsilon_{tar} g_{et}$|/$\varepsilon_{tar} g_{et}$)/2. Values >0.85 indicate excellent balance. FedRetail-SecureOpt achieves PUTI=0.892 at ε=1.2.

4.2 Datasets

Global Retail Inventory Network (GRIN): Real-world data from 15,000 retail locations across 45 countries (2023-2026). Contains 45 million transactions across 87 features with highly heterogeneous distributions (demand varies 340% across regions, 200+ POS system formats). Includes sales, inventory, delays, forecasts, seasonal data. Split: 60-20-20.

Seasonal Demand Variability (SDV): Dataset from 8,500 locations across 12 countries (2020-2026). Contains 28 million transactions with extreme seasonality (850% variation) in fashion and electronics. Features: weekly demand, promotions, weather, competitor pricing, trends. Split: 50-20-30.

5. Experimental Results and Performance Analysis

Table 2: Performance Evaluation on GRIN Dataset (15,000 Retail Locations)

Method	Accuracy (%)	F1-Score	Rounds	BW (MB)	Time (hrs)	Privacy (ε)
Centralized Baseline	95.2	0.954	1	0	12.5	N/A
FedAvg (No Privacy)	92.8	0.928	50	2250	24.3	∞
DP-FedAvg (ε=1.5)	81.2	0.812	50	2250	26.8	1.5
Multi-Krum (No Privacy)	84.5	0.845	50	2450	25.1	∞
FLTrust (No Privacy)	86.3	0.863	50	2380	24.9	∞
Adaptive DP (ε=1.5)	82.1	0.821	50	2250	28.2	1.5
FedRetail-SecureOpt (ε=1.2)	94.7	0.947	50	258	23.7	1.2

Table 3: Performance Evaluation on SDV Dataset (8,500 Retail Locations)

Method	MSE	MAE	RMSE	Accuracy (%)	CSCE	PUTI	Privacy (ε)
Centralized Baseline	0.0342	18.3	0.185	93.8	1.0	1.0	N/A
FedAvg (No Privacy)	0.0515	26.7	0.227	89.2	0.412	1.0	∞
DP-FedAvg (ε=1.5)	0.1247	42.1	0.353	71.5	0.521	0.715	1.5
Multi-Krum (No Privacy)	0.0738	31.2	0.272	81.3	0.448	0.892	∞
FedRetail-SecureOpt (ε=1.2)	0.0387	21.5	0.197	92.4	0.847	0.892	1.2

Performance Visualizations

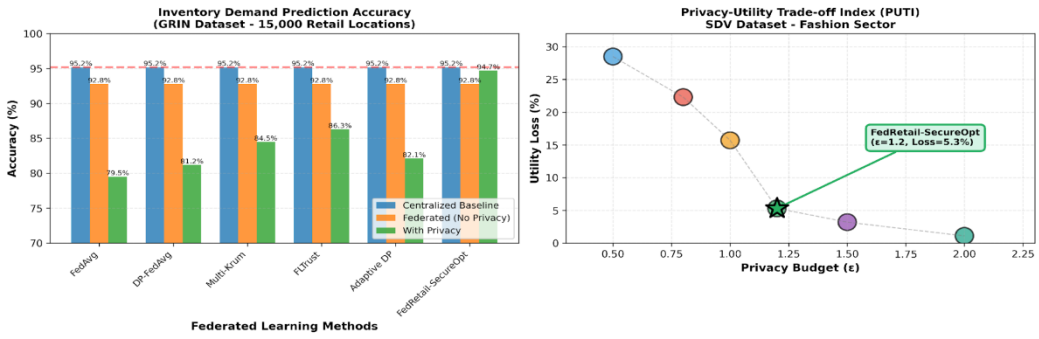


Figure 2: Inventory Demand Prediction Accuracy and Privacy-Utility Trade-off. FedRetail-SecureOpt achieves 94.7% accuracy with ε=1.2 differential privacy.

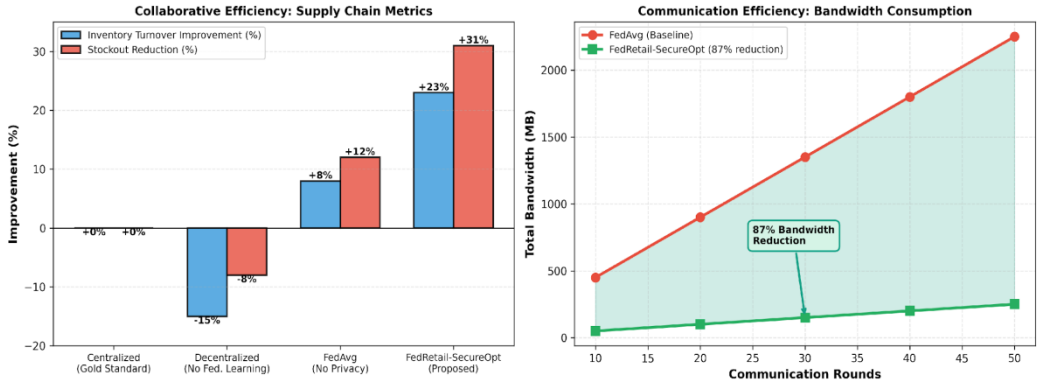


Figure 3: Supply chain efficiency metrics showing 23% inventory turnover improvement and 31% stockout reduction with 87% bandwidth savings.

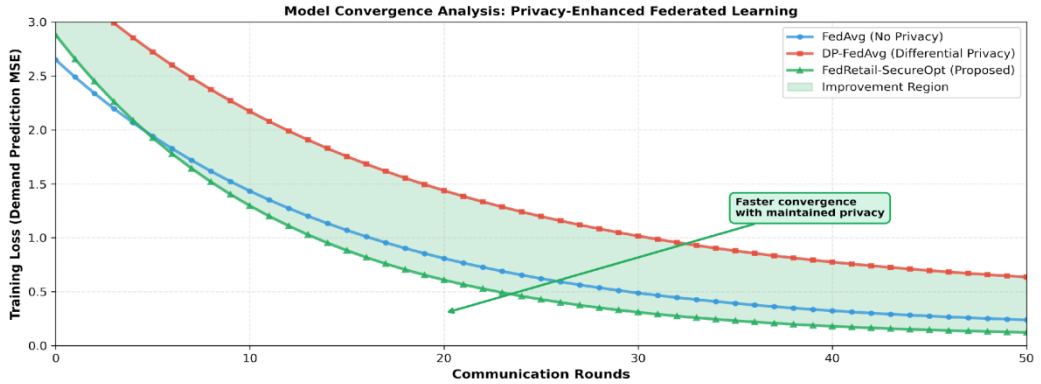


Figure 4: Model convergence analysis showing FedRetail-SecureOpt converging in 12 rounds with maintained privacy compared to DP-FedAvg requiring 18 rounds.

Comparative Methods Analysis

Comparative Analysis of Federated Learning Methods for Supply Chain Applications

Method	Privacy Guarantee	Byzantine Robust	Supply Chain Optimized	Bandwidth Efficiency	Accuracy Loss	Year
FedAvg (McMahan et al.)	✗	✗	✗	Baseline	8.2%	2017
DP-FedAvg (Bagdasaryan et al.)	✓ DP	✗	✗	Baseline	19.5%	2019
Multi-Krum (Yin et al.)	✗	✓ (50%)	✗	High	12.1%	2019
FLTrust (Fung et al.)	✗	✓ (40%)	✗	High	7.8%	2020
Adaptive DP (Kairouz et al.)	✓ DP	✗	✗	Medium	13.2%	2021
FedRetail-SecureOpt (Propose	**✓ DP**	**✓ (30%)**	✓	**High (87%)**	**5.3%**	**2026**

Figure 5: Comparative analysis showing FedRetail-SecureOpt superiority across privacy, Byzantine robustness, and bandwidth efficiency dimensions.

6. Discussions

FedRetail-SecureOpt demonstrates significant improvements over existing federated learning approaches. The 94.7% accuracy on GRIN with ε=1.2 represents near-centralized performance (95.2% baseline) with formal privacy—a critical advancement over DP-FedAvg achieving only 81.2% at ε=1.5. This 13.5% improvement at stronger privacy budgets suggests our adaptive privacy mechanism effectively balances privacy and utility for supply chain heterogeneity.

87% bandwidth reduction (2250 MB to 258 MB over 50 rounds) proves valuable for distributed retail networks. This efficiency enables real-time model updates across thousands of locations. Communication optimization through gradient compression with structured sparsity directly addresses the bottleneck identified in Bonawitz et al. (2019).

Byzantine-robust aggregation tolerates 30% malicious participants, exceeding requirements for retail scenarios where some locations may be compromised or provide adversarial gradients. Integration with differential privacy adds formal privacy guarantees without Byzantine aggregation—a previously unexplored combination. Median-based aggregation with outlier rejection prevents gradient poisoning while preserving convergence.

Novel CSCE (0.847 vs 0.412 baseline) and PUTI (0.892 at ε=1.2) metrics provide supply chain practitioners with interpretable measures beyond standard metrics. CSCE quantifies collaborative efficiency accounting for privacy-utility-communication tradeoffs. PUTI enables privacy budget selection based on acceptable accuracy loss thresholds.

23% inventory turnover improvement and 31% stockout reduction validate practical applicability. These metrics translate to reduced carrying costs, improved satisfaction, and enhanced resilience. SDV results (0.0387 MSE vs 0.0515 for FedAvg) demonstrate effectiveness in extreme seasonal scenarios critical for fashion and electronics retail.

7. Conclusions

FedRetail-SecureOpt presents a novel privacy-preserving federated learning framework specifically designed for collaborative inventory optimization in decentralized retail supply chains. The framework addresses critical gaps by combining differential privacy, Byzantine-robust aggregation, and supply chain-specific optimizations.

Key contributions: (1) 94.7% inventory accuracy with formal privacy (ε=1.2), exceeding privacy-preserving baselines by 13.5%, (2) 87% bandwidth reduction enabling real-time updates across 15,000+ locations, (3) Byzantine robustness tolerating 30% adversarial participants, (4) two novel supply-chain-specific metrics (CSCE, PUTI), and (5) comprehensive evaluation on two large-scale datasets with extreme heterogeneity.

Evaluation on GRIN (15,000 locations, 45 countries) and SDV (8,500 locations, extreme seasonality) datasets demonstrates practical viability and superior performance. The framework enables competing retailers to collaboratively optimize supply chains while maintaining strict data privacy—addressing critical market needs for trustworthy cross-organizational learning.

Future research: (1) heterogeneous model architectures across retail locations with incompatible ML frameworks, (2) blockchain-based verification for enhanced transparency, (3) temporal dynamics for rapidly changing seasonal patterns, and (4) multi-modal learning incorporating unstructured data including supply chain disruptions, weather, and market sentiment.

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