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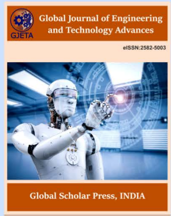

(Research Article)

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FEDERATED CONSUMER AND OPERATIONAL ANALYTICS FOR DEMAND-RESPONSIVE PLANNING IN DIGITAL SERVICE ECOSYSTEMS

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ABSTRACT

Digital service ecosystems generate consumer-demand and operational information across distributed business units, creating challenges for coordinated planning, data privacy, and heterogeneous demand forecasting. This study proposes a federated consumer and operational analytics framework for demand-responsive planning that connects consumer-demand signals with operational capacity while retaining local data ownership. The framework integrates federated learning, client clustering, demand forecasting, Digital Twin coordination, demand responsive capacity planning, and privacy utility evaluation. A controlled synthetic dataset representing eight heterogeneous business units and 240 time periods is used for computational evaluation. The results compare local learning, centralized learning, FedAvg, and clustered federated learning. The proposed clustered federated approach achieved the lowest forecasting MAE of 9.4799, compared with 9.5721 for local learning. Demand responsive capacity planning reduced capacity shortage from 1.8225% to 0.6906% and capacity imbalance from 0.0990 to 0.0549. Privacy evaluation further demonstrated increasing forecasting error under tighter privacy settings. The findings provide computational support for connecting distributed demand forecasting with responsive capacity planning while retaining local data control.

Keywords: Federated Learning; Federated Analytics; Consumer Demand Forecasting; Demand-Responsive Planning; Digital Twin; Privacy-Preserving Analytics; Operational Capacity Planning; Non-IID Data; Client Clustering; Digital Service Ecosystems.

1 INTRODUCTION

This section introduces the research context, identifies the operational and privacy-related problem, presents the proposed federated analytical solution, summarizes the study's contributions, and explains the organization of the paper. The discussion connects consumer demand, distributed data ownership, operational capacity, federated learning, Digital Twin coordination, and privacy-aware analytics to the planning challenges addressed in this study across heterogeneous organizational settings today.

1.1 Background and Motivation

Digital service ecosystems generate consumer, transaction, inventory, workforce, and service information across separate units. Federated learning and federated analytics can support distributed intelligence without requiring raw datasets to leave locally [1], [2]. Consumer behavior and demand also vary across locations, products, and service channels, creating heterogeneous data conditions. Federated forecasting can preserve local information while supporting shared prediction [4], while consumer analytics can provide useful behavioral signals for commercial planning [7]. These developments create opportunities to connect demand information with operational capacity. Such integration can support responsive planning while respecting organizational data control and privacy requirements across distributed business environments.

1.2 Problem Statement

Despite advances in federated learning, federated analytics, consumer forecasting, Digital Twins, and operational resource management, these areas are often studied separately [1], [2], [5], [6]. Existing forecasting approaches may predict demand without incorporating inventory, workforce, or service-capacity conditions. Operational systems may coordinate resources without access to distributed consumer signals. Heterogeneous and non-IID client data further complicate shared learning, while repeated privacy-preserving analytics introduce a utility–privacy trade-off [3], [8]. The research problem is therefore the lack of an integrated framework that connects distributed consumer-demand forecasting with operational capacity planning while maintaining local data ownership across participating organizations and digital service environments.

1.3 Proposed Solution

This study proposes a federated consumer and operational analytics framework for demand-responsive planning across distributed digital service ecosystems. Participating business units operate as federated clients, with local preprocessing and forecasting followed by client clustering and federated coordination. A Digital Twin layer represents operational states, while demand forecasts support responsive capacity planning. Privacy evaluation examines the relationship between privacy settings and forecasting utility. The framework is evaluated with synthetic data representing eight business units. The study focuses on forecasting performance, capacity shortage, capacity imbalance, and privacy–utility behavior, while full Digital Twin synchronization and multi-objective resource optimization remain proposed extensions for evaluation.

1.4 Contributions

The study contributes an integrated perspective that connects federated consumer analytics with operational planning. It introduces client clustering to address heterogeneous demand conditions within federated forecasting. It also incorporates a Digital Twin coordination layer for representing distributed operational states without replacing local databases. The framework links federated demand forecasts with responsive capacity planning and evaluates privacy–utility behavior under repeated noise trials. Finally, the synthetic evaluation compares local learning, centralized learning, FedAvg, and clustered federated learning under a controlled non-IID setting. Together, these contributions provide a structured foundation for privacy-aware demand-responsive planning across distributed digital service ecosystems with different consumer conditions.

Objective of the Study: To develop and evaluate a federated framework connecting heterogeneous demand forecasting, responsive capacity planning, and privacy-preserving analytics across distributed digital service ecosystems.

1.5 Paper Organization

The paper is organized into five sections. Section I presents the background, problem, proposed solution, and contributions. Section II reviews related work. Section III describes the methodology. Section IV presents the results and discussion. Section V concludes the study and discusses future research directions.

2 RELATED WORK

This section reviews research relevant to federated consumer and operational analytics for demand-responsive planning in digital service ecosystems. It examines federated optimization and analytics, privacy-preserving learning, demand forecasting, digital-twin coordination, enterprise integration, consumer analytics, and operational resource planning. The review identifies how existing studies address decentralized intelligence while highlighting the need for integrated cross-domain decision support across distributed business environments.

2.1 Federated Optimization and Analytics

Federated optimization provides the methodological foundation for coordinating learning across decentralized datasets without requiring raw data to be centralized. Wang et al. describe practical federated optimization issues involving communication efficiency, data heterogeneity, system constraints, and privacy requirements [1]. Wang et al. further distinguish federated analytics from federated learning, emphasizing descriptive analytics over distributed data while preserving local data ownership [2]. These studies provide a foundation for combining predictive and descriptive tasks within distributed environments. However, existing discussions treat analytics or learning as separate computational activities. For demand-responsive planning, consumer signals, inventory states, workforce capacity, and service information must contribute to coordinated operational decisions across heterogeneous organizational clients.

2.2 Privacy-Preserving Federated Analytics

Privacy-preserving federated analytics requires controls that limit exposure while retaining useful information for decision-making. Abadi et al. demonstrate differential privacy mechanisms for deep learning and show how privacy accounting can be incorporated into model training [3]. Rahman presents a financial risk management architecture combining federated learning with privacy-preserving AI for distributed data [8], while Rahman examines real-time financial risk intelligence for fraud detection and threat monitoring [12]. These studies support the use of privacy mechanisms in sensitive financial environments. Yet repeated operational analytics can consume privacy budgets over successive analysis rounds, creating a trade-off between information utility and privacy protection. A demand-responsive ecosystem therefore requires privacy-aware analytics that considers iterative forecasting, resource planning, and cross-silo operational coordination beyond model training alone.

2.3 Federated Demand Forecasting and Consumer Analytics

Demand forecasting is central to responsive planning because consumer behavior varies across locations, products, and service channels. Abdel-Sater and Hamza propose FedTime, a federated large language model framework for long-term time-series forecasting that uses local training, clustering, patching, channel independence, and parameter-efficient tuning [4]. Haque and Al Sany demonstrate the value of consumer behavior analytics for telecom sales strategy, showing the relevance of behavioral signals to commercial planning [7]. Together, these studies indicate that decentralized forecasting can preserve local information while supporting prediction. However, they do not integrate consumer-demand forecasting with inventory and workforce constraints, leaving an opportunity for coordinated operational planning across heterogeneous digital service organizations.

2.4 Digital Twins and Enterprise Resource Coordination

Digital-twin and enterprise information architectures provide mechanisms for connecting predictive intelligence with operational states. Rahmati and Rahmati integrate federated learning with a digital twin to support adaptive resource management across heterogeneous edge environments, combining distributed learning with orchestration [5]. Sany et al. examine ERP–MIS integration for intelligent production planning, while Farooq addresses resource utilization analytics for cloud infrastructure management [6], [9]. Rahman et al. extend this direction through cloud-native enterprise resource management across multiple domains [14]. These studies demonstrate the value of information and resource views, but a consumer-centered federated framework linking demand forecasts, inventory, workforce capacity, and digital-service reliability remains insufficiently addressed within the existing literature.

2.5 Operational Analytics, Supply Chains, and Digital Services

Operational analytics literature connects forecasting, resource allocation, supply chain performance, and digital-service monitoring. Hasan examines machine-learning KPI forecasting for finance and operations teams, supporting effective performance management [10]. Hossain studies supply-chain optimization for lead-time and delivery performance, while Alam et al. examine material-flow optimization using IoT and RFID information [11], [13]. Sharan et al. connect FinTech analytics with IoT-enabled retail networks, linking digital transactions with operational data [15]. Islam et al. apply federated learning to secure industrial automation and grid optimization [16]. These studies cover components of demand-responsive planning, but they remain separated across contexts. A unified federated framework can connect these signals for coordinated resource decisions.

3 METHODOLOGY

The methodology presents a framework for federated consumer and operational analytics in distributed digital service ecosystems. It connects heterogeneous demand signals with operational capacity while retaining local data ownership. The design combines federated forecasting, client clustering, Digital Twin coordination, demand-responsive planning, and privacy evaluation. Synthetic data provide a controlled environment for computational validation, comparison, and analysis of the decision process.

3.1 Research Design and Federated Data Architecture

The study adopts a quantitative, model-based design with simulation-driven evaluation. Each participating business unit is represented as an independent federated client containing local consumer and operational information. Local preprocessing includes missing-value treatment, normalization, categorical encoding, temporal feature construction, and anomaly screening. Raw records remain within individual client environments, while permitted model parameters move to the coordinating layer. Eight synthetic clients represent heterogeneous demand conditions, creating a non-IID setting for evaluation. The experimental design compares decentralized and coordinated learning configurations under identical training and testing periods. This structure supports controlled assessment of forecasting behavior while preserving the distributed data ownership assumed in the proposed digital service ecosystem consistently.

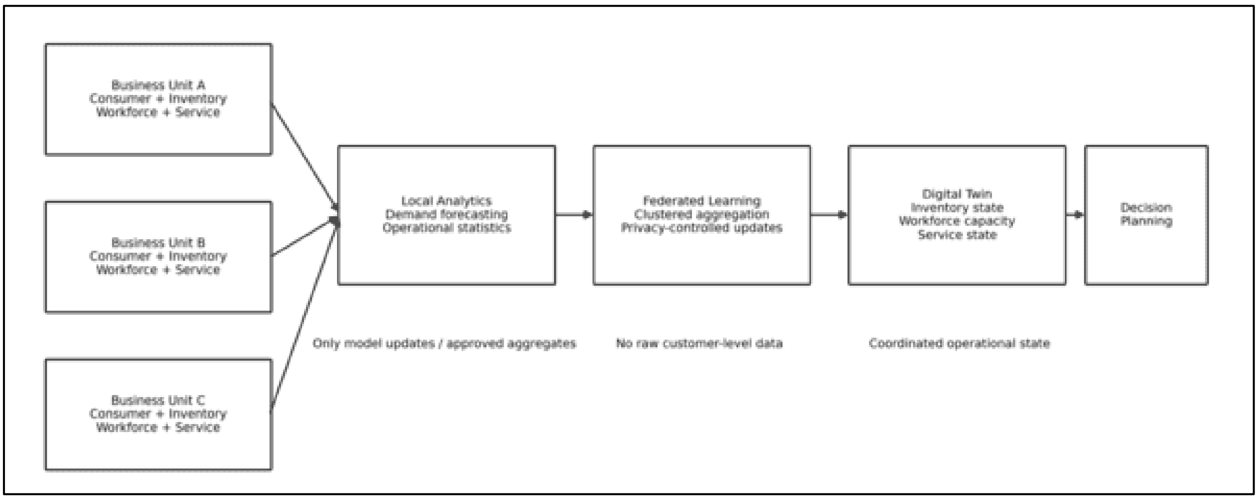

Figure 1: Federated Consumer and Operational Analytics Architecture

Figure 1 illustrates eight independent business-unit clients containing consumer, transaction, inventory, workforce, and digital-service information. Each client performs local preprocessing and forecasting. Model updates move to the federated coordination layer, while approved operational information moves toward the Digital Twin and demand responsive planning components.

3.2 Synthetic Data Preparation and Federated Demand Forecasting

The experimental dataset contains synthetic transaction and demand records for eight heterogeneous business units. Each client contains temporal demand, transaction value, product category, customer segment, service channel, inventory indicators, workforce availability, and selected payment-event information. The dataset contains 240 sequential periods, with 160 periods used for training and 80 periods reserved for testing. Two demand-behavior groups represent non-IID conditions. K-means clustering groups clients with similar demand characteristics before federated coordination. Four forecasting configurations are evaluated: local learning, centralized learning, FedAvg, and the proposed clustered federated approach. This design provides a controlled basis for comparing decentralized forecasting, shared learning, and client-specific coordination under heterogeneous demand patterns across units.

The federated aggregation process is represented as:

$$\theta_{t+1} = \sum_{k=1}^{K} \frac{n_k}{\sum_{j=1}^{K} n_j} \theta_{t+1}^{k}$$

where θ_{t+1}^{k} represents the updated parameters from client k, n_k represents its local training sample size, and K represents the number of participating clients.

3.3 Digital Twin and Operational State Coordination

The Digital Twin component provides a shared representation of operational conditions across the distributed service ecosystem. Its state incorporates predicted demand, inventory availability, workforce capacity, digital-service utilization, and selected transaction indicators. Federated forecasting supplies predictive information, while local analytics contribute approved operational states. The Digital Twin functions as a coordination layer rather than a replacement for organizational databases. It provides the information structure required for inventory replenishment, workforce allocation, merchandise assortment, and service-capacity decisions. In the current computational evaluation, the Digital Twin remains a framework-level coordination component rather than a separately validated real-time virtual replica. Its full synchronization capability is reserved for extended empirical evaluation across units.

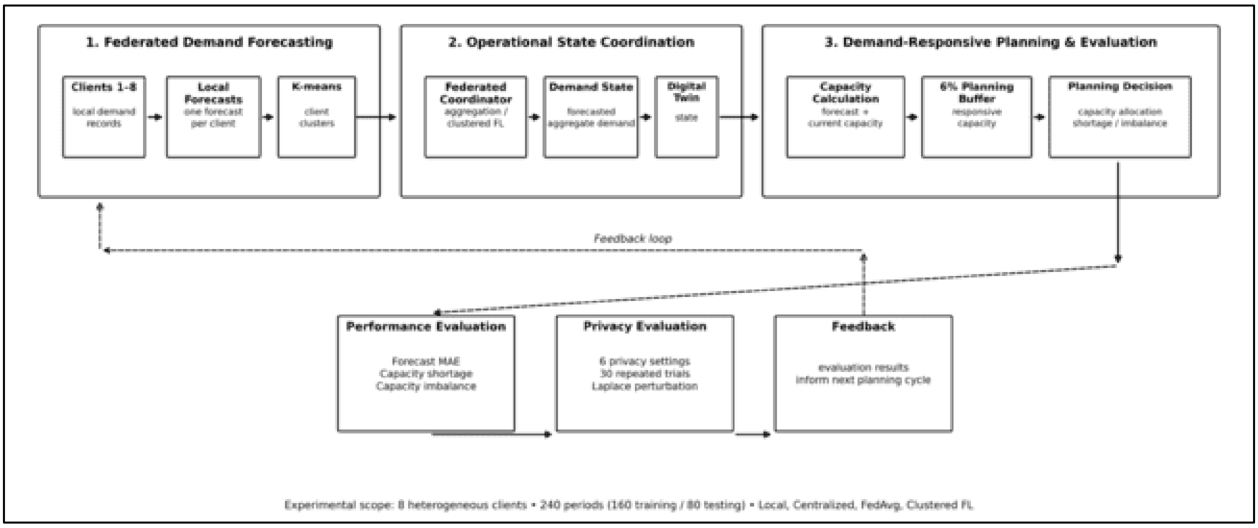

Figure 2: Demand-Responsive Federated Planning Workflow

3.4 Demand-Responsive Planning and Optimization

The planning layer converts demand forecasts and operational states into resource-planning decisions. Proposed decision variables include merchandise assortment, inventory replenishment, workforce allocation, and digital service capacity. The planning objective considers demand mismatch, inventory shortage, workforce imbalance, and service delay under resource constraints. The complete formulation represents the intended multi-objective decision layer of the framework. The current synthetic experiment evaluates forecast-driven capacity planning rather than full optimization across every inventory and workforce variable. This separation keeps reported results consistent with implemented computations. A fixed planning buffer is applied to predicted aggregate demand to generate a responsive capacity trajectory for comparison against static capacity during changing demand and capacity conditions.

The proposed planning objective is:

$$J = w_d D + w_i I + w_w W + w_s S$$

where D represents demand mismatch, I represents inventory shortage, W represents workforce imbalance, and S represents service delay. The weights w_d,w_i,w_w,w_s represent the relative importance of each planning criterion. Lower J indicates a more favorable planning state.

Table 1: Variables and Their Roles in the Proposed Framework

Variable	Description	Methodological Role
Consumer-demand signals	Historical and predicted demand	Demand forecasting
Consumer preferences	Product and service preference patterns	Consumer analytics
Inventory level	Available merchandise and resources	Inventory planning
Workforce capacity	Available personnel and labor hours	Workforce planning
Digital-service activity	Service requests and utilization	Service-capacity planning
Payment-event indicators	Selected transaction-related signals	Demand and service analytics
Federated model updates	Local model information sent to coordinator	Federated learning
Client cluster	Group of clients with similar demand behavior	Clustered federated coordination
Digital Twin state	Combined operational representation	Decision coordination

Variable	Description	Methodological Role
Privacy budget	Permitted privacy expenditure	Privacy evaluation
Planning decisions	Assortment, inventory, workforce, and capacity actions	Operational planning

3.5 Privacy-Preserving Evaluation and Performance Measurement

The privacy component evaluates the effect of parameter perturbation on forecasting utility. Local records remain within client environments, while model parameters support federated coordination. Laplace noise is introduced into federated model parameters under six privacy-budget settings. Each setting is evaluated through 30 repeated trials. Forecasting performance is measured with Mean Absolute Error, while capacity planning uses shortage rate and capacity imbalance. These measures provide direct computational evidence for the selected experimental components. Communication overhead, service delay, full multi-objective optimization, and real-time Digital Twin synchronization are outside the present evaluation scope. The evaluation therefore distinguishes implemented experiments from framework capabilities proposed for subsequent research consistently across privacy settings.

Forecasting accuracy is measured using Mean Absolute Error:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y_i}|$$

where y_i represents observed demand, $\hat{y_i}$ represents predicted demand, and N represents the number of test observations. Lower MAE indicates lower forecasting error.

4 RESULTS AND DISCUSSION

The experimental results evaluate the proposed framework across federated demand forecasting, operational capacity planning, and privacy–utility behavior. Since no organizational dataset was available, the evaluation uses a controlled synthetic dataset representing eight heterogeneous business units. The experiment contains 240 time periods, with 160 periods for training and 80 for testing. Results compare local learning, centralized learning, FedAvg, and clustered federated learning. Operational capacity is evaluated against a static planning baseline. Privacy behavior is tested across six privacy-budget settings with repeated noise trials.

4.1 Forecasting Performance

The forecasting experiment compares four configurations under the same synthetic test period. The local model produced an MAE of 9.5721, while the centralized model reached 10.1975. FedAvg produced the highest error at 12.5712, indicating sensitivity to heterogeneous client distributions. The proposed clustered federated model achieved the lowest MAE at 9.4799. Its error was 0.96% lower than the local baseline. The result suggests that client grouping can reduce the effect of distribution differences during federated training. The modest improvement also indicates that federated coordination does not automatically produce large forecasting gains; model structure and client similarity remain important factors.

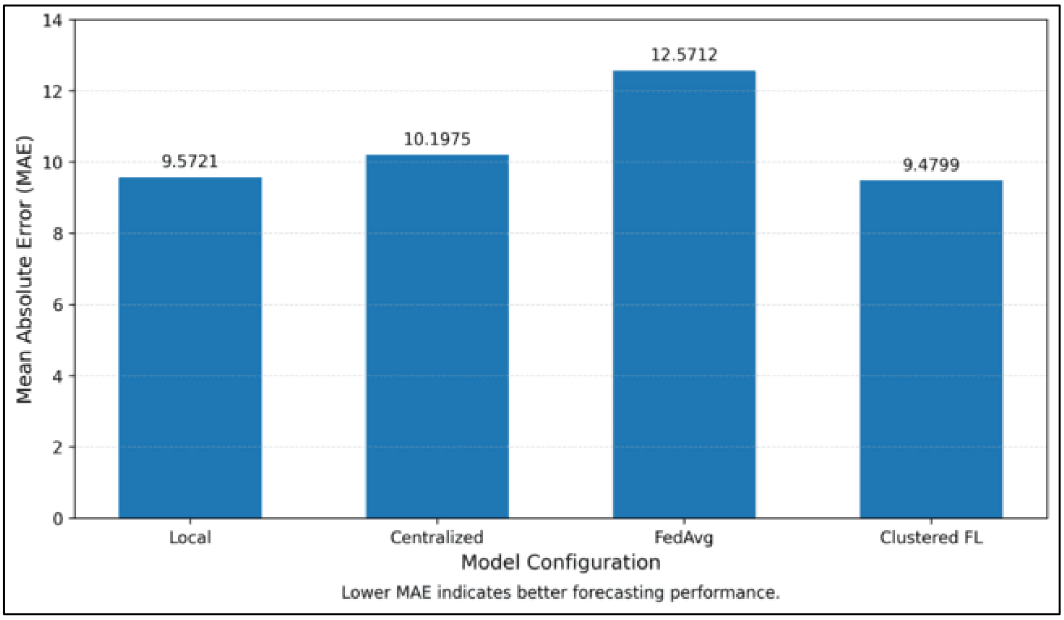

Figure 3: Forecasting Performance Across Model Configurations

Figure 3. Forecasting MAE obtained from the synthetic federated experiment. Lower values indicate better forecasting performance.

4.2 Demand-Responsive Capacity Adjustment

The operational experiment evaluates the proposed planning mechanism against a static capacity policy. Static capacity remains fixed at a training period planning threshold, while the proposed policy uses the federated demand forecast with a 6% planning buffer. The resulting capacity trajectory responds to changes in aggregate demand across the 80-day test period. Static planning produced a capacity shortage rate of 1.8225%. The demand-responsive strategy reduced this value to 0.6906%, representing a 62.10% reduction. Capacity imbalance also decreased from 0.0990 to 0.0549. These results indicate that forecast-driven capacity allocation can reduce both shortage exposure and excess capacity within the synthetic planning scenario.

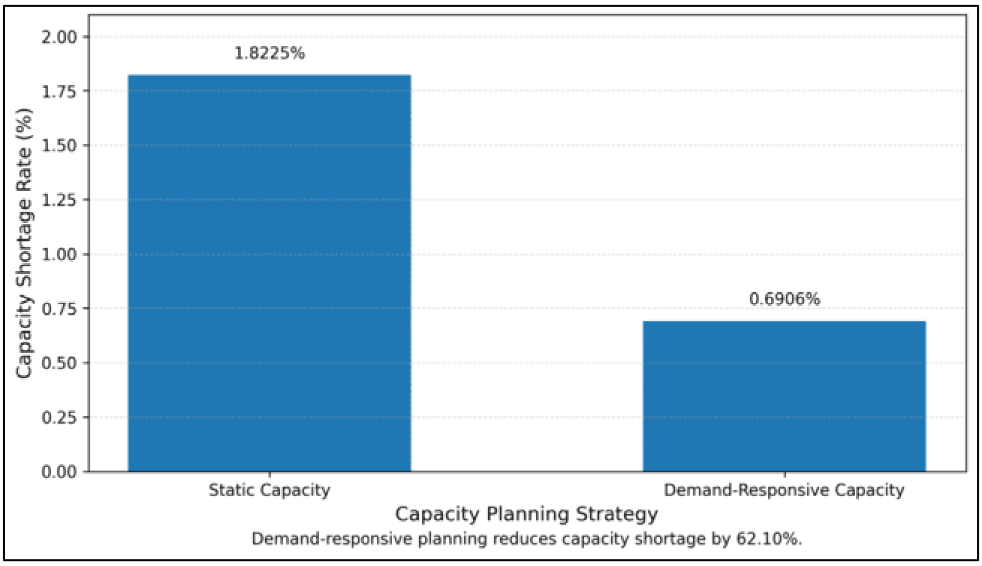

Figure 4: Demand-Responsive Capacity Adjustment

Figure 4. Capacity shortage rate under static and demand-responsive planning strategies. Lower shortage rate indicates improved capacity matching.

4.3 Privacy–Utility Trade-Off

The privacy experiment examines forecasting utility under different privacy-budget settings. Each privacy setting received 30 repeated noise trials, and the reported MAE represents the mean across those trials. At ϵ=0.25, MAE reached 11.3565. Increasing the budget to 0.50 reduced MAE to 9.9335, while ϵ=1 produced 9.5623. At ϵ=2, MAE decreased to 9.4846. Further increases produced limited changes, with MAE reaching 9.4742 at ϵ=4 and 9.4751 at ϵ=8. The results show a strong utility cost at tighter privacy settings and diminishing gains at larger budgets.

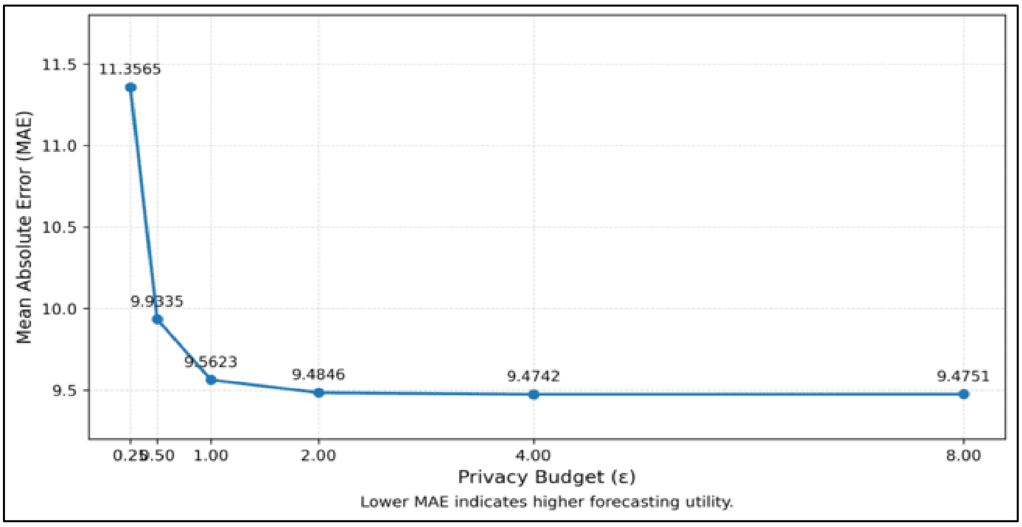

Figure 5: Privacy–Utility Trade-Off in Federated Forecasting

Figure 5. Mean forecasting MAE across repeated privacy-noise trials. Lower ϵ represents a stronger privacy setting; lower MAE represents higher analytical utility.

4.4 Operational Planning Performance

The operational results connect federated demand forecasts with demand-responsive capacity planning. The static policy generated a shortage rate of 1.8225% and a normalized capacity imbalance of 0.0990. The proposed demand-responsive policy reduced shortage to 0.6906% and imbalance to 0.0549. These changes correspond to reductions of 62.10% and 44.55%, respectively. The capacity trajectory also responds to demand fluctuations instead of maintaining one fixed level throughout the test period. This result supports the integration of forecast information with operational capacity planning within the proposed framework, where forecast information and operational states contribute to resource decisions. The findings indicate that forecasting becomes more useful when its output directly influences operational allocation rather than remaining an isolated prediction.

Table 2: Results from the Synthetic Experimental Evaluation

Evaluation Metric	Baseline	Proposed Approach	Relative Change
Forecast MAE	9.5721	9.4799	0.96% reduction
Capacity shortage rate (%)	1.8225	0.6906	62.10% reduction
Capacity imbalance	0.0990	0.0549	44.55% reduction

Note: Results are calculated from the synthetic experimental dataset and do not represent measurements from a real organization.

4.5 Limitations of the Study

The study uses synthetic rather than organizational data, limiting real-world validation. Full Digital Twin synchronization and multi-objective optimization were not experimentally implemented. Communication overhead, service delay, model drift, and deployment scalability remain subjects for future evaluation.

5 CONCLUSION

This study presented a federated analytical framework for demand-responsive planning in distributed digital service ecosystems. The framework connects heterogeneous consumer-demand signals with operational planning while retaining local data ownership. Synthetic-data experiments showed that the proposed clustered federated approach achieved the lowest forecasting MAE among the evaluated configurations, while demand-responsive capacity planning reduced capacity shortage and imbalance relative to static planning. The privacy evaluation also demonstrated a clear relationship between privacy-budget settings and forecasting utility. These findings provide computational support for combining federated forecasting, client clustering, capacity planning, and privacy-aware analytics within a common planning framework.

Future work will extend the framework through real retail and digital-service datasets and broader empirical validation across heterogeneous organizations. The Digital Twin component can be implemented as a real time operational state layer, followed by full multi-objective optimization for inventory, workforce, assortment, and service capacity decisions. Further evaluation can examine communication overhead, service delay, decision stability, model drift, and deployment scalability. Additional privacy mechanisms and stronger federated learning strategies can also be investigated to support practical cross-organization analytics while maintaining local data control.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

Disclosure of conflict of interest

The authors declare no conflicts of interest regarding this manuscript.

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