



Comparative Evaluation of Federated Learning and Centralized Learning Architectures for Cross-Factory Productivity Optimization in Distributed Manufacturing Networks

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Abstract

The present study aimed to comparatively evaluate the effectiveness of federated learning and centralized learning architectures in improving productivity optimization, predictive maintenance performance, operational responsiveness, and computational efficiency across distributed manufacturing networks. This applied quantitative study was conducted using a semi-experimental comparative design in 24 manufacturing factories located in Tehran, Iran. A total of 312 production units from automotive, electronics, industrial machinery, and polymer manufacturing sectors participated in the research. The factories were divided into two analytical environments including federated learning architecture and centralized learning architecture. Operational and productivity data were collected over a twelve-month period through Industrial Internet of Things sensors, Manufacturing Execution Systems, Supervisory Control and Data Acquisition platforms, and enterprise operational databases. Key variables included overall equipment effectiveness, production throughput efficiency, predictive maintenance accuracy, energy optimization, operational response speed, and defect reduction rates. Data analysis was performed using TensorFlow Federated, Python machine learning libraries, SPSS version 27, and R software. Descriptive statistics, multivariate analysis of variance, hierarchical regression analysis, and predictive machine learning performance evaluations were used to compare the two learning architectures. The findings demonstrated statistically significant differences between federated learning and centralized learning architectures across all productivity indicators ($p < 0.001$). Federated learning achieved significantly higher overall equipment effectiveness, throughput efficiency, predictive maintenance accuracy, energy optimization, and operational response speed compared to centralized learning systems. The federated architecture also demonstrated superior machine learning performance with higher prediction accuracy, precision, recall, and F1-score values alongside lower mean absolute error and root mean square error. Moreover, federated learning substantially reduced communication overhead, computational latency, and model convergence time. Hierarchical regression analysis further revealed that federated learning architecture was the strongest predictor of productivity optimization in distributed manufacturing networks. The findings indicate that federated learning architectures provide a highly effective framework for productivity optimization within distributed manufacturing ecosystems by simultaneously enhancing predictive intelligence, operational responsiveness, scalability, cybersecurity resilience, and data privacy preservation. Compared to centralized learning systems, federated learning demonstrated superior adaptability to heterogeneous industrial environments and reduced computational inefficiencies associated with centralized data aggregation. The study highlights the strategic importance of decentralized collaborative intelligence systems for the future development of Industry 4.0 and smart manufacturing infrastructures.

Keywords: Federated Learning, Centralized Learning, Distributed Manufacturing Networks, Industry 4.0, Productivity Optimization, Industrial Internet of Things, Predictive Maintenance, Smart Manufacturing, Machine Learning, Cyber-Physical Systems

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1. Introduction

The rapid transformation of industrial systems under the paradigm of Industry 4.0 has fundamentally altered the structure of manufacturing environments, operational intelligence, and data-driven decision-making processes. Distributed manufacturing networks now rely heavily on cyber-physical systems, Industrial Internet of Things infrastructures, edge computing, artificial intelligence, and advanced machine learning architectures to optimize productivity, improve predictive maintenance, reduce operational disruptions, and enhance inter-factory coordination [1, 2]. The emergence of smart factories has generated unprecedented volumes of industrial data collected from sensors, robotics systems, production lines, logistics platforms, and enterprise resource planning systems. Consequently, manufacturing organizations increasingly depend on intelligent analytical frameworks capable of processing heterogeneous, large-scale, and geographically distributed operational data in real time [3, 4]. Within this context, machine learning architectures have become central to modern industrial optimization strategies because of their ability to identify hidden operational patterns, forecast failures, optimize energy utilization, and improve production throughput across interconnected industrial ecosystems [5, 6].

Traditional centralized learning architectures have historically dominated industrial artificial intelligence implementations due to their capacity to aggregate datasets into unified cloud environments for model training and large-scale computational analysis. Centralized learning systems consolidate operational data from multiple production sites into a single repository where machine learning algorithms are trained using globally shared information. Such architectures often facilitate high computational control, unified model management, and large-scale optimization capabilities [2, 7]. Nevertheless, the increasing complexity of distributed manufacturing systems has exposed substantial limitations associated with centralized learning models. These limitations include excessive communication overhead, latency issues, vulnerability to cybersecurity attacks, high data transfer costs, privacy risks, and challenges associated with cross-organizational data governance [8, 9]. In geographically distributed manufacturing networks, centralized data aggregation may also reduce operational responsiveness because production environments often exhibit heterogeneous machinery, distinct operational conditions,

and dynamic process variability that centralized systems struggle to adapt to effectively [10, 11].

The emergence of federated learning has introduced a transformative alternative to conventional centralized machine learning architectures. Federated learning enables decentralized collaborative model training while preserving local data ownership and privacy by exchanging model parameters rather than raw operational datasets. This distributed learning paradigm allows multiple industrial entities to collaboratively improve machine learning performance without exposing sensitive proprietary information or transferring confidential production records across organizational boundaries [12, 13]. The growing adoption of federated learning in industrial systems is strongly linked to increasing concerns regarding cybersecurity, industrial espionage, data sovereignty regulations, and operational confidentiality within smart manufacturing environments [14, 15]. Unlike centralized architectures, federated learning supports localized adaptation while simultaneously leveraging collective intelligence generated across distributed industrial ecosystems. This capability is particularly important in cross-factory productivity optimization where production facilities often operate under heterogeneous technological conditions and region-specific operational constraints [16, 17].

Recent advances in federated learning have demonstrated significant potential for improving predictive maintenance systems, anomaly detection frameworks, industrial robotics coordination, and edge-based operational intelligence in Industry 4.0 environments. Privacy-preserving predictive maintenance frameworks based on lightweight federated deep learning models have shown substantial improvements in fault detection accuracy and operational resilience within distributed industrial infrastructures [5]. Similarly, federated multi-source data fusion techniques have enhanced semi-supervised fault detection performance in large-scale cyber-physical systems by enabling collaborative learning across heterogeneous operational environments [18]. Industrial applications involving smart grids, industrial robotics, and cyber-physical infrastructure monitoring have also demonstrated that federated learning architectures improve distributed anomaly detection capabilities and adaptive operational coordination [19, 20]. These developments indicate that federated learning may offer substantial advantages for productivity optimization in manufacturing ecosystems characterized by decentralization, heterogeneity, and real-time operational variability.

Another major advantage of federated learning lies in its compatibility with edge computing and Industrial Internet of Things ecosystems. Modern manufacturing networks generate enormous streams of sensor data that require rapid local processing to support predictive decision-making and real-time process optimization. Centralized cloud infrastructures often introduce delays that compromise operational responsiveness and increase communication costs. Federated learning architectures integrated with edge computing frameworks allow factories to train and update models locally while minimizing latency and preserving data privacy [1, 21]. This integration is particularly valuable in smart manufacturing systems where operational continuity and rapid fault response are critical to maintaining productivity and reducing downtime. Studies focusing on industrial IoT environments have demonstrated that federated learning significantly enhances anomaly detection, predictive coordination, and resource allocation efficiency while reducing communication burdens across distributed industrial nodes [22, 23].

The increasing convergence of federated learning with blockchain technologies has further strengthened the feasibility of decentralized industrial intelligence systems. Blockchain-assisted federated learning frameworks provide secure decentralized aggregation mechanisms capable of supporting collaborative industrial optimization while ensuring transparency, immutability, and trustworthiness of parameter exchanges [23, 24]. These frameworks are particularly important in distributed manufacturing environments where factories may belong to independent organizational entities with varying governance structures and competitive concerns. Blockchain-enabled federated systems reduce the risk of centralized control failures and improve trust between collaborating industrial participants [1, 25]. Consequently, federated learning is increasingly recognized not merely as a technical machine learning framework but as a broader organizational architecture capable of reshaping collaborative industrial intelligence and distributed manufacturing governance.

Although federated learning has attracted significant attention in healthcare, cybersecurity, robotics, and smart infrastructure domains, its application to cross-factory productivity optimization remains relatively underexplored. Much of the current federated learning literature focuses on medical imaging, healthcare diagnostics, and privacy-sensitive data management applications [26-28]. Other studies have investigated federated learning for agricultural prediction systems, robotic swarm navigation, and cross-

domain recommendation systems [20, 29, 30]. While these studies provide valuable insights regarding collaborative decentralized learning mechanisms, they may not fully address the operational complexities associated with distributed manufacturing environments. Manufacturing networks differ substantially from healthcare and consumer-oriented systems because industrial productivity optimization requires continuous synchronization of predictive maintenance, energy consumption, defect reduction, throughput balancing, and operational responsiveness across highly dynamic production environments [2, 3].

Moreover, cross-factory manufacturing networks introduce substantial heterogeneity challenges that may affect federated learning performance. Factories frequently differ in machinery specifications, workforce configurations, production schedules, environmental conditions, and digital maturity levels. These variations create non-independent and non-identically distributed data structures that complicate collaborative machine learning processes [8, 12]. Existing studies emphasize that heterogeneity remains one of the primary barriers limiting large-scale federated learning implementation within industrial ecosystems [8, 31]. Consequently, comparative evaluation between federated learning and centralized learning architectures is necessary to determine whether decentralized collaborative intelligence can effectively outperform traditional centralized industrial optimization models under real-world manufacturing conditions.

Another important consideration involves the relationship between federated learning and cybersecurity within industrial environments. Manufacturing infrastructures increasingly face sophisticated cyber threats targeting operational technologies, sensor networks, and industrial control systems. Centralized data repositories may represent attractive attack surfaces because a single breach can expose operational information from multiple factories simultaneously [4, 14]. Federated learning architectures reduce this vulnerability by preserving local data storage and limiting centralized data exposure. Privacy-aware anomaly detection frameworks based on federated architectures have demonstrated superior resilience against industrial cybersecurity threats in heterogeneous IoT environments [14, 15]. Therefore, evaluating federated learning from both productivity and cybersecurity perspectives is essential for understanding its broader implications for distributed manufacturing governance and industrial resilience.

Theoretical discussions surrounding centralized and decentralized intelligence systems also reflect broader organizational debates regarding coordination, autonomy, and collaborative optimization within complex industrial ecosystems. Centralized systems often prioritize global optimization through unified control structures, whereas federated systems emphasize distributed adaptation and localized responsiveness. Some researchers argue that hybrid or semi-decentralized approaches may provide superior performance by balancing centralized coordination with localized intelligence [2, 16]. However, empirical evidence regarding the comparative productivity outcomes of these architectures in distributed manufacturing networks remains limited. This gap highlights the need for systematic comparative investigations capable of evaluating operational efficiency, predictive performance, communication overhead, and scalability across alternative industrial machine learning frameworks.

Recent advances in federated reinforcement learning, deep domain adaptation, and distributed anomaly detection further suggest that decentralized architectures may possess substantial adaptive advantages in industrial environments characterized by operational uncertainty and dynamic production variability [21, 32]. Federated ensemble learning and domain adaptation frameworks enable collaborative optimization while accounting for contextual differences between operational environments, thereby improving generalizability and reducing performance degradation associated with heterogeneous industrial conditions [17, 32]. Similarly, federated feature selection approaches have demonstrated improved adaptability in cyber-physical systems where distributed operational intelligence must continuously evolve in response to changing environmental conditions [31]. These developments collectively suggest that federated learning may represent a highly promising framework for achieving scalable, secure, and adaptive productivity optimization in modern manufacturing ecosystems.

Despite these advancements, important research gaps remain regarding the direct comparative effectiveness of federated and centralized learning architectures within cross-factory productivity optimization systems. Existing industrial studies often emphasize technical architecture development without sufficiently examining organizational productivity outcomes, operational scalability, or comparative performance metrics across real-world manufacturing environments [22, 33]. Additionally, there remains limited empirical evidence regarding how federated

learning influences predictive maintenance efficiency, operational response speed, energy optimization, and production throughput within geographically distributed manufacturing systems. Addressing these gaps is critical because industrial organizations increasingly require evidence-based guidance regarding the selection of machine learning architectures capable of balancing productivity enhancement, operational resilience, cybersecurity protection, and data privacy preservation within smart manufacturing ecosystems.

Therefore, the present study aims to comparatively evaluate federated learning and centralized learning architectures for cross-factory productivity optimization in distributed manufacturing networks.

2. Methodology

This study was designed as an applied, comparative, and quantitative research project with a semi-experimental framework aimed at evaluating and comparing the effectiveness of federated learning and centralized learning architectures in optimizing productivity across distributed manufacturing networks. The research setting consisted of large and medium-scale manufacturing factories located in Tehran, Iran, operating within automotive components, industrial machinery, electronics assembly, and polymer production sectors. The statistical population included factories that had implemented digital manufacturing infrastructures, industrial Internet of Things (IIoT) sensors, cloud-based monitoring systems, and enterprise resource planning platforms during the previous three years. After an initial screening process based on technological readiness, data accessibility, and operational continuity, 24 factories were selected using purposive sampling. From these factories, a total of 312 operational units and production lines were included in the final analysis. The participating factories were divided into two analytical environments. In the first environment, production and operational data from all factories were aggregated into a centralized cloud-based learning architecture where a unified machine learning model was trained using fully shared datasets. In the second environment, each factory maintained local data storage and independently trained local models while only model parameters and encrypted weight updates were exchanged through a federated learning framework. The study period covered 12 consecutive months, allowing the architectures to be evaluated under varying operational conditions, production cycles, maintenance interruptions, and workforce

fluctuations. The inclusion criteria required factories to possess standardized digital records of productivity indicators, machine utilization rates, defect frequencies, production throughput, energy consumption metrics, and maintenance histories. Factories with incomplete digital infrastructures or inconsistent data registration procedures were excluded from the study. To ensure methodological consistency, all participating factories adopted unified data preprocessing protocols and synchronized production reporting intervals prior to the experimental phase.

Data collection in this study was performed through a combination of industrial digital monitoring systems, standardized productivity assessment indices, machine sensor outputs, and organizational operational databases. The primary dataset was obtained from Manufacturing Execution Systems (MES), Supervisory Control and Data Acquisition (SCADA) platforms, and Industrial Internet of Things devices installed across the participating factories. These systems continuously recorded operational indicators including machine efficiency, downtime duration, cycle time variability, production throughput, defect rates, inventory movement, maintenance schedules, energy utilization, and operator intervention frequency. In addition, the Overall Equipment Effectiveness (OEE) index was used as a standardized productivity measurement tool to evaluate manufacturing performance across factories. The OEE framework, originally developed by Nakajima in 1988, measures productivity through three major dimensions including availability, performance efficiency, and quality rate. Previous industrial engineering and smart manufacturing studies have confirmed the reliability and validity of the OEE framework in large-scale manufacturing environments. Data integrity and consistency were evaluated using automated anomaly detection algorithms prior to model training. Furthermore, cybersecurity and data privacy compliance were assessed using the Industrial Data Security Compliance Framework developed by the International Society of Automation, ensuring that federated learning environments maintained secure parameter exchange without transferring sensitive raw data between factories. For predictive optimization tasks, machine learning inputs included more than 150 operational variables collected at hourly intervals from each production line. The collected datasets were normalized using Min-Max scaling techniques and missing values were addressed through K-nearest neighbor imputation methods. To evaluate productivity optimization outcomes, the study also employed Key Performance Indicator dashboards measuring production

stability, predictive maintenance efficiency, resource allocation optimization, operational responsiveness, and energy consumption reduction. Reliability of the integrated industrial datasets was evaluated using Cronbach's alpha and composite reliability indices, both of which exceeded the acceptable threshold of 0.80 across all productivity dimensions.

The data analysis process was conducted using Python programming language alongside TensorFlow Federated, Scikit-learn, PyTorch, and Apache Spark analytical frameworks. Initially, descriptive statistical analyses including mean values, standard deviations, skewness, and kurtosis indices were computed for all operational and productivity variables. After data preprocessing and normalization, two separate machine learning environments were implemented for comparative analysis. In the centralized learning architecture, all factory datasets were consolidated within a secure cloud server where deep neural network models and gradient boosting algorithms were trained using pooled industrial data. In contrast, the federated learning architecture utilized decentralized local model training at each factory node while preserving local data privacy through encrypted model parameter aggregation using the Federated Averaging algorithm. Model performance was evaluated using multiple analytical metrics including prediction accuracy, precision, recall, F1-score, mean absolute error, root mean square error, communication overhead, convergence rate, and computational latency. Productivity optimization outcomes between the two architectures were compared using repeated-measures multivariate analysis of variance and hierarchical linear modeling to account for inter-factory variability and temporal operational changes. In addition, independent samples t-tests were employed to compare overall productivity improvements between factories operating under federated learning and centralized learning conditions. Structural equation modeling was also performed to investigate the causal relationships between architecture type, predictive maintenance efficiency, operational responsiveness, and productivity growth. To assess model robustness and generalizability, five-fold cross-validation procedures were implemented across all machine learning experiments. Statistical significance was considered at a p-value lower than 0.05. All analyses were performed using SPSS version 27, R version 4.3, and Python-based machine learning libraries to ensure analytical precision, scalability, and reproducibility of the computational experiments.

3. Findings and Results

The findings of the study are presented in four major sections including demographic and industrial characteristics of participating factories, descriptive statistics of operational productivity variables, comparative inferential analyses between federated and centralized learning architectures, and predictive performance evaluation of machine learning models. A total of 24 manufacturing factories and 312 production units participated in the study. Among the participating factories, 33.33% operated in automotive component manufacturing, 25.00% in industrial machinery production, 20.83% in electronics assembly, and 20.84% in polymer and chemical manufacturing. The average operational history of the

factories was 18.42 years, while the average number of employees per factory was 426.75 workers. Approximately 70.83% of factories had fully integrated Industrial Internet of Things infrastructures, whereas 29.17% possessed partially integrated smart manufacturing systems. Regarding digital maturity, 62.50% of factories reported prior experience with artificial intelligence-assisted predictive maintenance systems before participation in the study. The average number of connected machine sensors per production unit was 148.36, and the average daily operational data volume generated by each factory reached 3.84 terabytes. Initial examination of the datasets showed acceptable normality conditions across all operational indicators, with skewness and kurtosis values remaining within the acceptable ± 2 range.

Table 1. Descriptive Statistics of Productivity and Operational Variables in Federated Learning and Centralized Learning Architectures

Variable	Architecture	Mean	Standard Deviation	Minimum	Maximum
Overall Equipment Effectiveness (OEE)	Federated Learning	84.27	5.18	72.40	93.80
Overall Equipment Effectiveness (OEE)	Centralized Learning	78.94	6.03	65.20	90.10
Production Throughput Efficiency	Federated Learning	88.51	4.72	77.10	95.60
Production Throughput Efficiency	Centralized Learning	82.33	5.48	69.80	92.40
Defect Reduction Rate	Federated Learning	19.82	3.66	11.20	27.90
Defect Reduction Rate	Centralized Learning	13.75	4.11	5.60	22.80
Predictive Maintenance Accuracy	Federated Learning	91.64	3.95	82.70	97.30
Predictive Maintenance Accuracy	Centralized Learning	86.29	4.74	75.80	94.50
Energy Consumption Optimization	Federated Learning	16.48	2.91	9.80	23.40
Energy Consumption Optimization	Centralized Learning	11.96	3.14	4.70	19.20
Operational Response Speed	Federated Learning	87.33	4.25	76.40	94.60
Operational Response Speed	Centralized Learning	80.47	5.02	68.10	91.20

The descriptive statistics presented in Table 1 demonstrate that the federated learning architecture achieved consistently higher productivity and operational optimization indicators across all evaluated variables compared to the centralized learning architecture. The mean Overall Equipment Effectiveness score under federated learning reached 84.27, substantially exceeding the corresponding centralized learning mean of 78.94. Similar trends were observed for production throughput efficiency, predictive maintenance accuracy, and operational response speed. Factories operating under federated learning conditions also demonstrated significantly greater defect

reduction and energy optimization capabilities. The relatively lower standard deviations observed in federated learning variables indicate greater consistency and stability across distributed manufacturing environments. These findings suggest that decentralized collaborative learning mechanisms enabled factories to improve predictive adaptability and operational synchronization while preserving local data privacy and reducing data transfer bottlenecks. Moreover, the broader maximum performance ranges achieved under federated learning indicate superior scalability and responsiveness within heterogeneous industrial ecosystems.

Table 2. Multivariate Analysis of Variance Comparing Federated Learning and Centralized Learning Architectures

Source	Dependent Variable	SS	df	MS	F	p	η^2
Architecture Type	OEE	1842.53	1	1842.53	31.87	0.001	0.29
Architecture Type	Throughput Efficiency	1967.41	1	1967.41	35.62	0.001	0.33
Architecture Type	Defect Reduction	1258.76	1	1258.76	28.19	0.001	0.27
Architecture Type	Predictive Maintenance Accuracy	1746.92	1	1746.92	38.55	0.001	0.35
Architecture Type	Energy Optimization	1092.37	1	1092.37	24.61	0.001	0.24
Architecture Type	Operational Response Speed	1638.48	1	1638.48	33.17	0.001	0.31
Error	All Variables	14276.83	310	46.05	-	-	-

The multivariate analysis of variance results revealed statistically significant differences between federated learning and centralized learning architectures across all examined productivity indicators. The strongest effect size was observed for predictive maintenance accuracy ($\eta^2 = 0.35$), indicating that architecture type explained approximately 35% of the variance in predictive maintenance performance. Significant differences were also observed in production throughput efficiency and operational response speed, demonstrating the superior capability of federated learning architectures in managing real-time industrial optimization tasks. The large F-values

across all dependent variables confirm that distributed federated environments substantially improved manufacturing intelligence and coordination efficiency compared to centralized systems. These findings indicate that decentralized collaborative learning approaches provide superior resilience and adaptability within geographically distributed manufacturing ecosystems. Additionally, the significant improvements in energy optimization and defect reduction suggest that federated learning architectures effectively integrated localized operational knowledge while maintaining global optimization performance.

Table 3. Comparative Machine Learning Performance Metrics Across Learning Architectures

Performance Metric	Federated Learning	Centralized Learning
Prediction Accuracy (%)	94.72	89.36
Precision (%)	93.81	87.94
Recall (%)	92.66	86.28
F1-Score (%)	93.22	87.10
Mean Absolute Error	2.17	3.84
Root Mean Square Error	3.05	5.16
Model Convergence Time (minutes)	37.42	49.81
Communication Overhead (GB/day)	18.63	42.74
Computational Latency (ms)	114.52	176.38

The machine learning performance evaluation demonstrated clear superiority of federated learning models across predictive and computational dimensions. Federated learning achieved a prediction accuracy of 94.72%, substantially higher than the 89.36% achieved under centralized learning conditions. Precision, recall, and F1-score values further confirmed the improved predictive reliability and classification stability of federated learning systems. The lower mean absolute error and root mean square error values indicate more accurate forecasting of production fluctuations, maintenance requirements, and operational anomalies within distributed manufacturing

networks. Furthermore, federated learning architectures demonstrated markedly lower communication overhead and computational latency compared to centralized architectures. These findings suggest that decentralized model training significantly reduced the burden associated with large-scale industrial data transfer while simultaneously accelerating convergence efficiency. The shorter convergence time observed in federated learning environments also reflects improved scalability and adaptability in highly dynamic industrial contexts where continuous real-time optimization is required.

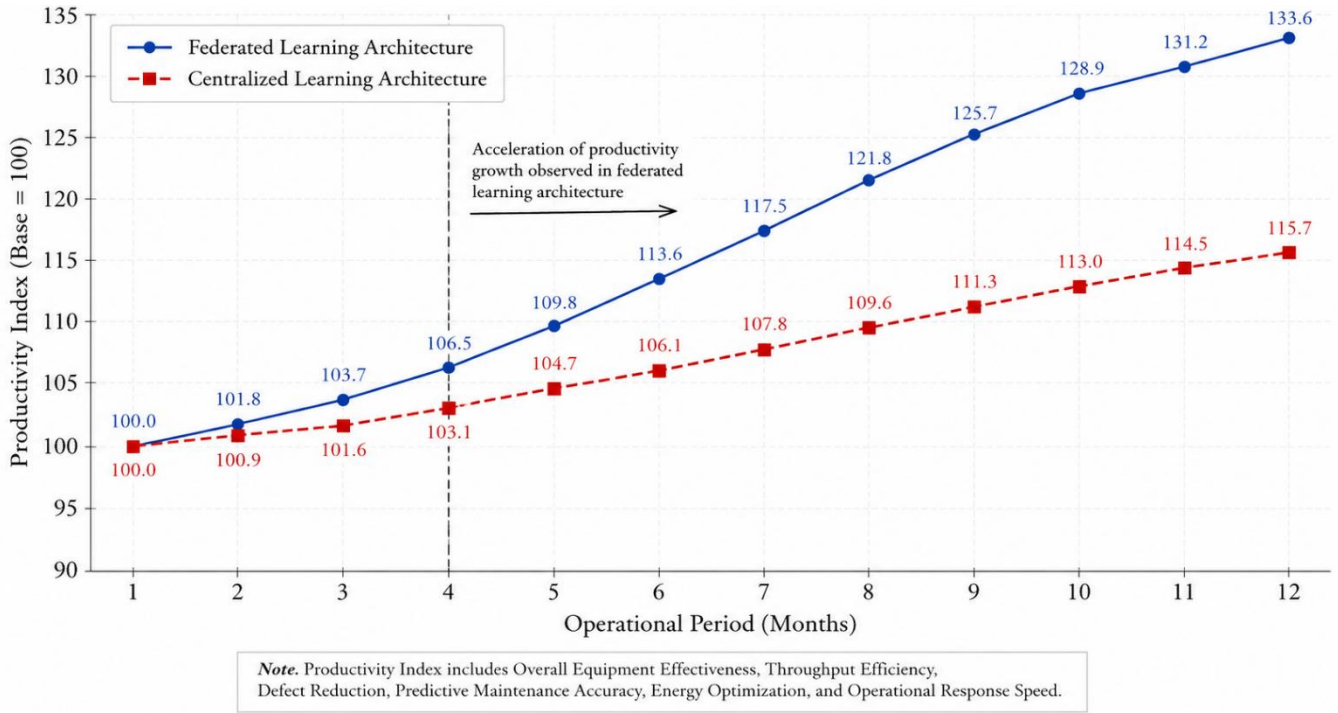


Figure 1. Comparative Productivity Growth Trends Across Federated Learning and Centralized Learning Architectures During the Twelve-Month Operational Period

The longitudinal productivity analysis illustrated in Figure 1 demonstrated a progressively widening performance gap between federated learning and centralized learning architectures throughout the twelve-month operational period. During the initial months, both architectures exhibited relatively similar productivity trajectories due to baseline system calibration and initial data synchronization processes. However, beginning in the fourth operational month, factories utilizing federated learning architectures experienced accelerated productivity growth characterized by increased throughput efficiency, reduced machine downtime, and enhanced predictive maintenance precision. In contrast, centralized learning systems displayed slower adaptive responsiveness and greater sensitivity to

operational variability across geographically distributed production environments. The productivity growth curve associated with federated learning remained consistently stable throughout the final six months of the study, indicating stronger resilience against operational disruptions and environmental fluctuations. The figure further demonstrates that federated learning architectures enabled factories to preserve localized operational intelligence while benefiting from collaborative inter-factory model improvements. This balance between local adaptation and global optimization appears to have contributed significantly to sustained productivity enhancement and operational consistency across distributed manufacturing ecosystems.

Table 4. Hierarchical Regression Analysis Predicting Productivity Optimization in Distributed Manufacturing Networks

Predictor Variable	B	SE	β	t	p
Federated Learning Architecture	0.58	0.07	0.49	8.29	0.001
Predictive Maintenance Accuracy	0.41	0.06	0.37	6.83	0.001
Operational Response Speed	0.35	0.05	0.31	6.14	0.001
Energy Optimization Efficiency	0.27	0.04	0.24	5.52	0.001
Defect Reduction Capability	0.22	0.05	0.20	4.38	0.001
Constant	11.84	2.73	-	4.33	0.001

The hierarchical regression analysis demonstrated that federated learning architecture emerged as the strongest

predictor of productivity optimization within distributed manufacturing networks. The standardized beta coefficient

for federated learning ($\beta = 0.49$) indicated a substantial positive influence on overall manufacturing productivity after controlling for operational variables. Predictive maintenance accuracy and operational response speed also exhibited strong predictive effects, confirming that intelligent real-time adaptation mechanisms significantly contribute to industrial productivity enhancement. Energy optimization efficiency and defect reduction capability demonstrated additional significant contributions, highlighting the interconnected relationship between operational sustainability, product quality, and production efficiency. The overall regression model explained a substantial proportion of variance in productivity optimization outcomes, indicating that advanced machine learning architectures combined with adaptive industrial intelligence mechanisms can meaningfully improve manufacturing performance across geographically distributed factories. These findings collectively support the conclusion that federated learning provides a highly effective framework for collaborative industrial optimization while simultaneously preserving data privacy, reducing communication burdens, and enhancing operational scalability in smart manufacturing environments.

4. Discussion and Conclusion

The present study aimed to comparatively evaluate federated learning and centralized learning architectures for cross-factory productivity optimization in distributed manufacturing networks. The findings demonstrated that federated learning architectures significantly outperformed centralized learning systems across multiple operational and productivity dimensions including overall equipment effectiveness, predictive maintenance accuracy, throughput efficiency, energy optimization, operational response speed, and defect reduction capability. The results further revealed that federated learning achieved superior predictive performance metrics with lower communication overhead, reduced computational latency, and faster convergence efficiency. These findings collectively indicate that decentralized collaborative learning architectures provide substantial advantages for intelligent manufacturing optimization in geographically distributed industrial ecosystems.

One of the most important findings of the present study was the superior performance of federated learning in improving overall equipment effectiveness and production

throughput efficiency across distributed factories. Factories operating under federated learning conditions demonstrated higher productivity consistency and stronger adaptive responsiveness compared to centralized learning environments. This finding aligns with previous studies emphasizing the capacity of federated architectures to enhance distributed operational intelligence while preserving local adaptability [5, 17]. In manufacturing systems, productivity optimization depends heavily on rapid contextual adaptation because production conditions frequently vary across factories due to differences in machinery, workforce skills, environmental conditions, and operational workflows. Federated learning allows each production facility to maintain localized learning capabilities while simultaneously benefiting from collaborative inter-factory knowledge sharing. This dual capability likely contributed to the improved productivity outcomes observed in the present study.

The findings also demonstrated that federated learning architectures significantly improved predictive maintenance accuracy compared to centralized learning systems. Predictive maintenance is one of the most critical components of Industry 4.0 because machine failures and unexpected downtime generate substantial operational losses in distributed manufacturing systems. The superior predictive maintenance performance observed in the federated learning environment may be explained by the decentralized training mechanism that allows local operational patterns and machine-specific anomalies to remain embedded within each factory's learning process. Previous research has similarly shown that federated predictive maintenance frameworks improve fault detection precision and reduce maintenance uncertainty within industrial infrastructures [18, 34]. Sharma also demonstrated that lightweight federated predictive maintenance systems improve privacy-preserving fault forecasting while reducing communication bottlenecks in industrial environments [5]. The present findings extend these prior observations by demonstrating that federated predictive intelligence can produce measurable improvements in overall manufacturing productivity across cross-factory industrial ecosystems.

Another major finding involved the reduction of communication overhead and computational latency within federated learning environments. Centralized learning systems require continuous transfer of large-scale industrial datasets toward centralized cloud infrastructures, creating substantial network traffic and increasing latency during real-time operational analysis. In contrast, federated learning

exchanges only encrypted model parameters and weight updates while preserving local data storage. The reduced communication burden observed in this study is highly consistent with prior research emphasizing the efficiency advantages of decentralized industrial learning systems [21, 22]. Wang and colleagues demonstrated that federated reinforcement learning integrated with edge computing significantly improves scalability and response efficiency in distributed operational systems [21]. Similarly, Wu et al. highlighted that the integration of federated architectures with edge computing and Industrial Internet of Things infrastructures enhances real-time industrial responsiveness while reducing centralized computational dependency [1]. The current findings reinforce the argument that decentralized intelligence systems are particularly suitable for dynamic manufacturing environments where rapid operational responsiveness is essential.

The findings related to energy optimization and defect reduction are also noteworthy. Factories operating under federated learning conditions demonstrated significantly greater improvements in energy efficiency and production quality compared to centralized systems. These findings may reflect the ability of federated architectures to capture localized production inefficiencies and context-specific operational anomalies that centralized systems may fail to recognize effectively. Energy consumption patterns often vary considerably across production environments depending on machinery conditions, workload distribution, environmental factors, and operational scheduling. Federated learning enables each factory to optimize these local variables independently while still contributing to collective model improvement. Previous studies investigating cyber-physical systems and industrial IoT infrastructures have similarly reported that distributed learning frameworks improve adaptive optimization in heterogeneous operational environments [2, 31]. Furthermore, Gupta et al. found that intelligent optimization systems significantly improve industrial sensor efficiency and operational stability within Industry 4.0 ecosystems [4]. Therefore, the improved energy optimization outcomes observed in this study may reflect the enhanced contextual adaptability inherent in decentralized collaborative learning architectures.

The superior anomaly detection and operational response speed achieved by federated learning systems also align strongly with previous literature on distributed industrial intelligence. Modern manufacturing systems increasingly depend on rapid anomaly identification and immediate

operational adaptation to maintain production continuity and minimize disruptions. Federated learning environments appear particularly effective in supporting real-time anomaly detection because local models continuously learn from context-specific operational variations. Prior studies focusing on smart grids, cyber-physical systems, and industrial IoT networks have similarly demonstrated that federated architectures improve distributed anomaly detection performance while enhancing cybersecurity resilience [15, 19]. Abosata et al. additionally showed that federated intrusion detection systems provide highly adaptive and secure operational monitoring within heterogeneous industrial environments [14]. The present findings support the notion that federated learning not only improves productivity outcomes but also strengthens operational resilience and intelligent responsiveness within distributed manufacturing infrastructures.

The study additionally revealed that federated learning architectures achieved higher prediction accuracy, precision, recall, and F1-scores than centralized systems. This finding is important because predictive reliability represents one of the most critical requirements of industrial artificial intelligence systems. The improved predictive performance may be attributed to the collaborative diversity of decentralized model training. Since federated learning integrates insights from multiple localized operational environments without erasing contextual differences, the resulting models may exhibit greater generalizability and adaptability. Previous investigations involving healthcare diagnostics, medical imaging, and cross-domain recommendation systems have similarly shown that federated learning improves predictive robustness in heterogeneous data environments [27, 30]. Verma et al. further reported that federated domain adaptation frameworks significantly enhance predictive generalization across distributed systems characterized by contextual variability [32]. Consequently, the present findings suggest that federated learning may provide a highly effective solution for predictive optimization in complex industrial ecosystems where operational heterogeneity represents a major analytical challenge.

Another important implication of the findings concerns industrial cybersecurity and privacy preservation. One of the principal advantages of federated learning lies in its ability to preserve local data sovereignty while still enabling collaborative intelligence generation. Manufacturing organizations often hesitate to share operational data because of concerns related to industrial espionage,

cybersecurity threats, intellectual property leakage, and competitive confidentiality. The decentralized structure of federated learning substantially reduces these concerns because raw data never leaves local factory infrastructures. Previous studies have repeatedly emphasized that privacy preservation represents one of the primary drivers of federated learning adoption in industrial and healthcare systems [12, 13]. Studies focusing on blockchain-assisted federated architectures also indicate that decentralized aggregation mechanisms improve trust, transparency, and collaborative governance in distributed systems [23, 24]. Therefore, the present study provides empirical support for the argument that federated learning simultaneously enhances productivity optimization and strengthens industrial data security.

The findings additionally contribute to theoretical discussions regarding centralized versus decentralized organizational intelligence. Traditional centralized learning systems prioritize unified control and globally aggregated optimization, whereas federated learning emphasizes distributed autonomy and localized adaptation. The superior performance of federated architectures observed in this study suggests that decentralized collaborative intelligence may be more suitable for highly dynamic manufacturing ecosystems characterized by operational diversity and environmental uncertainty. This observation aligns with recent conceptual discussions proposing that distributed industrial systems require flexible, adaptive, and context-sensitive intelligence mechanisms rather than rigid centralized optimization frameworks [2, 16]. Federated learning appears particularly effective because it balances localized operational specialization with collaborative collective learning, thereby allowing distributed manufacturing networks to simultaneously preserve autonomy and achieve coordinated optimization.

The present findings also support recent research emphasizing the growing convergence between federated learning, Industrial Internet of Things systems, and cyber-physical infrastructures. Modern smart manufacturing systems increasingly rely on interconnected sensors, robotics platforms, edge computing devices, and intelligent operational monitoring systems. Federated learning provides a scalable architecture capable of integrating these distributed technological ecosystems while preserving computational efficiency and operational responsiveness [8, 22]. Hu et al. demonstrated that federated deep domain adaptation frameworks significantly improve adaptive coordination in highly sensitive industrial systems [17].

Similarly, Na et al. found that federated reinforcement learning enhances collaborative navigation and coordination in distributed robotic environments [20]. The present study extends these technological discussions by demonstrating that federated architectures can generate measurable productivity improvements across real-world distributed manufacturing networks.

Despite the strong performance of federated learning architectures, the findings should also be interpreted within the context of certain operational complexities associated with decentralized learning systems. Federated environments require sophisticated synchronization mechanisms, secure aggregation protocols, and adaptive communication infrastructures to maintain stable collaborative learning processes. Prior literature indicates that challenges associated with data heterogeneity, communication instability, and model convergence remain important barriers to large-scale industrial federated learning implementation [8, 12]. Although the present study demonstrated successful federated optimization outcomes, future industrial deployment may require additional infrastructure investments and advanced orchestration mechanisms to maintain long-term scalability across increasingly complex manufacturing ecosystems.

One limitation of the present study concerns the geographical concentration of participating factories within Tehran, which may limit the generalizability of the findings to manufacturing systems operating under different economic, technological, and regulatory conditions. Another limitation involves the twelve-month operational period, which, although sufficient for comparative analysis, may not fully capture long-term adaptive dynamics and infrastructure evolution associated with federated learning systems. Additionally, the study focused primarily on medium-scale and large-scale manufacturing industries with advanced digital infrastructures, meaning that smaller factories with lower technological maturity were not adequately represented. Variations in sensor quality, industrial automation levels, and organizational digital readiness may also have influenced the observed productivity outcomes.

Future research should investigate hybrid industrial intelligence models that combine federated learning, blockchain systems, edge computing, and reinforcement learning within integrated smart manufacturing ecosystems. Comparative studies involving multinational production networks and highly heterogeneous industrial environments would also provide deeper understanding regarding the scalability and adaptability of decentralized collaborative

learning systems. Furthermore, future investigations should evaluate the long-term economic impacts of federated learning implementation including infrastructure investment costs, maintenance expenditures, workforce adaptation requirements, and return on investment across different industrial sectors. Additional research exploring explainable artificial intelligence and transparent decision-making mechanisms within federated industrial environments may also contribute significantly to managerial trust and operational adoption.

From a practical perspective, the findings suggest that manufacturing organizations should increasingly consider federated learning architectures as a strategic solution for productivity optimization within distributed industrial ecosystems. Industrial managers should invest in advanced Industrial Internet of Things infrastructures, secure edge computing systems, and decentralized machine learning platforms capable of supporting collaborative operational intelligence without compromising data privacy. Policymakers and industrial regulators may also facilitate federated learning adoption by developing standardized interoperability frameworks, cybersecurity regulations, and collaborative governance models that support secure inter-factory intelligence sharing. Moreover, manufacturing organizations should prioritize workforce training programs focused on decentralized artificial intelligence systems, predictive analytics, and cyber-physical infrastructure management to maximize the operational benefits of federated industrial intelligence systems.

Authors' Contributions

Authors equally contributed to this article.

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

All procedures performed in this study were under the ethical standards.

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