Article history:
Received 19 February 2026
Revised 08 June 2026
Accepted 11 June 2026
Initial Pubish 01 July 2026
Published online 01 September 2026

Journal of Resource Management and Decision Engineering

Volume 5, Issue 5, pp 1-12

Integrated Queue Management and Service Composition for Enhancing Manufacturing-as-a-Service Performance

Mina. Ravanesh[1], Emad. Roghanian[2*]

[1] PHD candidate of industrial engineering, K. N. Toosi University of Technology, Tehran, Iran
[2] Associate Professor of industrial engineering, K. N. Toosi University of Technology, Tehran, Iran

*** Corresponding author email address**: m.ravanesh@email.kntu.ac.ir

A r t i c l e I n f o

Article type:
Original Research

How to cite this article:
Ravanesh, M., & Roghanian, E. (2026). Integrated Queue Management and Service Composition for Enhancing Manufacturing-as-a-Service Performance. *Journal of Resource Management and Decision Engineering*, *5*(5), 1-12.
https://doi.org/10.61838/kman.jrmde.359

A B S T R A C T

This study aimed to develop and empirically evaluate an integrated framework examining the effects of integrated queue management and service composition capability on Manufacturing-as-a-Service (MaaS) performance, while assessing the enabling role of technological support factors within service-oriented manufacturing environments. This applied quantitative study employed a descriptive-correlational design using structural equation modeling. The statistical population consisted of manufacturing managers, industrial engineers, production planners, and digital manufacturing specialists working in manufacturing organizations in Tehran, Iran. A total of 384 participants were selected through stratified random sampling. Data were collected using a researcher-developed questionnaire measuring integrated queue management, service composition capability, technological support factors, and MaaS performance. Content validity was confirmed by an expert panel, while construct validity was assessed through confirmatory factor analysis. Reliability was established using Cronbach's alpha, composite reliability, and average variance extracted indicators. Data analysis was performed using SPSS 27 and SmartPLS 4. The measurement model demonstrated satisfactory reliability and validity, with Cronbach's alpha values ranging from 0.887 to 0.925, composite reliability values between 0.909 and 0.938, and average variance extracted values exceeding 0.50 for all constructs. Structural equation modeling revealed that integrated queue management had a significant positive effect on MaaS performance ($\beta = 0.421$, $t = 8.974$, $p < 0.001$). Service composition capability also exerted a significant positive effect on MaaS performance ($\beta = 0.366$, $t = 7.852$, $p < 0.001$). Technological support factors significantly influenced MaaS performance directly ($\beta = 0.214$, $t = 4.986$, $p < 0.001$) and indirectly through their effects on integrated queue management ($\beta = 0.492$, $t = 9.843$, $p < 0.001$) and service composition capability ($\beta = 0.547$, $t = 11.308$, $p < 0.001$). The proposed model explained 68.7% of the variance in MaaS performance ($R^2 = 0.687$), indicating substantial explanatory power and predictive relevance. The findings demonstrate that integrated queue management and service composition capability are critical drivers of Manufacturing-as-a-Service performance, while technological support factors provide the essential infrastructure enabling their effectiveness.

Keywords: *Manufacturing-as-a-Service, Queue Management, Service Composition, Service-Oriented Manufacturing*

1. Introduction

The rapid digital transformation of manufacturing systems has fundamentally changed the way production resources are organized, managed, and delivered across industrial ecosystems. Traditional manufacturing environments, characterized by fixed production capacities, isolated resources, and rigid operational structures, are increasingly being replaced by flexible and service-oriented architectures that emphasize interoperability, scalability, and dynamic resource sharing. Within this context, Manufacturing-as-a-Service (MaaS) has emerged as a promising paradigm that enables manufacturing resources, capabilities, and production services to be offered and consumed in a manner analogous to cloud-based computing services. By leveraging distributed infrastructures, intelligent networking technologies, and service-oriented architectures, MaaS allows organizations to access manufacturing capabilities on demand while improving resource utilization, operational agility, and production efficiency (Taleb et al., 2023; Zeydan & Mangues-Bafalluy, 2022).

The growing complexity of industrial production systems has intensified the need for sophisticated mechanisms capable of coordinating heterogeneous manufacturing services across distributed environments. Modern manufacturing networks often involve multiple service providers, production facilities, logistics systems, computational resources, and intelligent devices that must operate collaboratively to satisfy dynamic customer demands. As the number of interconnected services increases, organizations face significant challenges related to service selection, task allocation, workflow orchestration, and operational synchronization. These challenges are particularly evident in MaaS environments where production requests must be dynamically matched with available manufacturing resources while ensuring optimal performance and minimal delays. Recent developments in service-oriented architectures and distributed systems have highlighted the importance of intelligent orchestration frameworks for managing increasingly complex service ecosystems (Garcia-Alonso, 2025; Horstmann et al., 2024; S., 2024).

One of the most critical operational challenges affecting MaaS environments is queue management. In distributed manufacturing systems, production requests frequently compete for limited resources, resulting in waiting times, bottlenecks, resource contention, and reduced operational efficiency. Ineffective queue management can lead to increased lead times, lower throughput, underutilization of resources, and diminished customer satisfaction. Consequently, organizations are seeking innovative approaches that can dynamically prioritize tasks, allocate resources efficiently, and optimize workflow execution. Advances in data engineering and distributed networking technologies have demonstrated that intelligent queue management mechanisms can significantly enhance the performance of complex service-oriented systems by enabling adaptive scheduling, real-time monitoring, and automated workload balancing (He et al., 2025; Romanov et al., 2023; Zeydan & Mangues-Bafalluy, 2022).

The concept of service composition has also attracted considerable attention as a means of improving operational effectiveness in distributed environments. Service composition refers to the process of combining multiple independent services into integrated workflows capable of delivering complex functionalities. In manufacturing systems, service composition enables organizations to coordinate production resources, logistics services, quality assurance functions, and computational capabilities within a unified operational framework. Effective service composition facilitates greater flexibility, adaptability, and responsiveness, allowing manufacturing systems to react efficiently to changing production requirements and market conditions. Recent studies have emphasized that advanced service composition frameworks represent a fundamental component of next-generation digital ecosystems and distributed service architectures (Garcia-Alonso, 2025; Kelliher et al., 2024; Shen, 2025).

The emergence of cloud-native technologies, microservices architectures, and serverless computing has further accelerated the evolution of service composition methodologies. These technologies enable organizations to deploy modular, scalable, and reusable service components that can be dynamically assembled according to operational requirements. Dynamic function configuration mechanisms have been shown to support efficient resource allocation and service adaptability in highly distributed environments. Similarly, event-driven architectures facilitate real-time communication among distributed services, allowing organizations to respond rapidly to operational changes and system events. Such capabilities are particularly relevant in MaaS environments where production requests, resource availability, and customer requirements may fluctuate continuously (Agarwal, 2025; Arafat, 2025; Bernard, 2025).

Recent advances in distributed computing have demonstrated the value of intelligent orchestration systems for coordinating complex workflows. Workflow orchestration mechanisms provide automated control over service interactions, task sequencing, and resource allocation decisions. Through centralized or decentralized coordination approaches, orchestration frameworks help ensure that distributed services operate cohesively while minimizing inefficiencies and operational disruptions. Research on distributed systems has consistently indicated that effective orchestration contributes to enhanced scalability, reliability, and performance across a wide range of application domains. These findings suggest that similar benefits may be achieved in MaaS environments through the integration of advanced orchestration and queue management strategies (Ahmadvand et al., 2026; Jani & Jani, 2024; S., 2024).

The increasing adoption of artificial intelligence and intelligent automation technologies has created new opportunities for optimizing manufacturing service ecosystems. AI-enabled orchestration frameworks are capable of analyzing operational conditions, predicting workload patterns, and dynamically adapting resource allocation strategies in response to changing circumstances. Recent developments in adaptive workflow management and compound AI systems have demonstrated significant improvements in efficiency, scalability, and decision-making performance. Such capabilities are particularly valuable in manufacturing environments where rapid adaptation to fluctuating production demands is essential for maintaining competitiveness and operational effectiveness (Gravara et al., 2026; Jiang et al., 2026; Xiao, 2026).

Furthermore, advances in cloud orchestration and distributed resource management have provided valuable insights into the optimization of large-scale service ecosystems. Studies examining Kubernetes-based infrastructures, serverless architectures, and distributed processing frameworks have highlighted the importance of efficient workload distribution and adaptive resource scheduling. These technologies enable organizations to improve resource utilization while maintaining service quality and operational resilience. The principles underlying these approaches can be effectively applied to MaaS environments, where manufacturing resources must be dynamically allocated to meet diverse production requirements (He et al., 2025; Kandpal et al., 2024; Malleni et al., 2026).

Another important consideration in modern service-oriented systems is fault tolerance and resilience. Manufacturing operations frequently encounter disruptions arising from equipment failures, communication breakdowns, fluctuating workloads, and unexpected environmental conditions. Consequently, resilient service architectures capable of maintaining operational continuity under adverse conditions have become increasingly important. Research on modular and fault-tolerant systems has demonstrated that robust orchestration mechanisms and adaptive resource management strategies can significantly improve system reliability and service availability. These findings underscore the necessity of incorporating resilience considerations into MaaS performance optimization frameworks (Dobaj et al., 2023; Guru et al., 2026; Singh, 2026).

The convergence of cyber-physical systems, digital twins, industrial Internet of Things technologies, and distributed computing infrastructures has further expanded the potential of MaaS implementations. These technologies facilitate real-time visibility into manufacturing operations and support intelligent decision-making across distributed production networks. Digital twins, in particular, provide powerful capabilities for monitoring, simulation, and predictive optimization, enabling organizations to evaluate alternative scheduling and service composition strategies before implementation. Such innovations create opportunities for integrating queue management and service composition mechanisms within comprehensive performance enhancement frameworks (Bernard, 2025; Dobaj et al., 2023; Thajchayapong, 2025).

Despite significant advances in service-oriented architectures, distributed computing, workflow orchestration, and intelligent resource management, important gaps remain in the literature regarding the integrated application of queue management and service composition within MaaS environments. Existing studies have frequently examined resource allocation, workflow orchestration, service composition, and performance optimization as separate research domains. Comparatively limited attention has been devoted to understanding how intelligent queue management mechanisms interact with service composition capabilities to jointly influence manufacturing service performance. Moreover, empirical evidence regarding the combined effects of these factors within industrial MaaS settings remains relatively scarce. Given the increasing complexity of distributed manufacturing ecosystems and the growing demand for efficient resource utilization, a comprehensive examination of these relationships is both theoretically and practically warranted (Gravara et al., 2026; Malvankar et al., 2026; Mantha et al., 2026).

Addressing these challenges requires the development of integrated frameworks capable of simultaneously optimizing resource allocation, service orchestration, workflow coordination, and operational responsiveness. Such frameworks must leverage advances in distributed computing, intelligent automation, event-driven architectures, and adaptive scheduling while remaining applicable to real-world manufacturing environments. Understanding the interplay between queue management and service composition can provide valuable guidance for practitioners seeking to enhance production efficiency, reduce operational delays, improve service quality, and strengthen organizational competitiveness within increasingly digitalized industrial ecosystems (Arafat, 2025; Singh, 2026; Xiao, 2026).

Therefore, the aim of this study was to develop and empirically evaluate an integrated framework of queue management and service composition for enhancing Manufacturing-as-a-Service performance in manufacturing organizations.

2. Methods and Materials

This study employed an applied research approach with a quantitative methodology to investigate the effects of integrated queue management and service composition on Manufacturing-as-a-Service (MaaS) performance. The research was conducted using a descriptive-correlational design and structural equation modeling to examine the relationships among the study variables and to develop a comprehensive framework for improving operational performance in MaaS environments. The statistical population consisted of managers, industrial engineers, production planners, manufacturing systems specialists, digital manufacturing consultants, and senior experts working in manufacturing firms and smart production centers located in Tehran, Iran. These organizations had adopted or were in the process of implementing digital manufacturing technologies, cloud manufacturing systems, industrial Internet of Things platforms, and service-oriented production architectures. Using Cochran's sample size formula for finite populations and considering a confidence level of 95%, a sample of 384 participants was determined to be sufficient for the study. Participants were selected through stratified random sampling to ensure adequate representation from different industrial sectors, including automotive manufacturing, electronics production, metal industries, machinery manufacturing, and advanced manufacturing enterprises. Inclusion criteria required participants to possess at least three years of professional experience in manufacturing operations or industrial service management and to have familiarity with digital manufacturing systems and service-oriented production environments.

Data were collected using a researcher-developed questionnaire designed based on an extensive review of the literature on Manufacturing-as-a-Service, queue management systems, service composition, cloud manufacturing, production scheduling, and operational performance optimization. The questionnaire consisted of four major dimensions. The first dimension assessed integrated queue management practices, including dynamic scheduling, workload balancing, resource allocation efficiency, waiting-time reduction mechanisms, queue prioritization strategies, and adaptive task assignment. The second dimension evaluated service composition capabilities, including service discovery, service selection, service orchestration, interoperability, flexibility, and composability of manufacturing services. The third dimension measured operational performance indicators, including production efficiency, service responsiveness, resource utilization, throughput improvement, lead-time reduction, and system reliability. The fourth dimension examined organizational and technological support factors, including information system integration, digital infrastructure readiness, technological compatibility, and managerial support for service-oriented manufacturing. All questionnaire items were measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). To establish content validity, the instrument was reviewed by a panel of fifteen experts specializing in industrial engineering, operations management, cloud manufacturing, and digital production systems. Their feedback was incorporated into the final version of the questionnaire. Construct validity was subsequently assessed through confirmatory factor analysis. Reliability was evaluated using Cronbach's alpha coefficient and composite reliability indices, both of which exceeded the recommended threshold of 0.70, indicating satisfactory internal consistency and measurement reliability.

Additional organizational data were gathered from participating companies to provide contextual information regarding production capacity, level of digitalization, manufacturing service utilization, and operational characteristics. These supplementary data were used to enhance the interpretation of findings and to support the validation of the proposed conceptual framework. Prior to the main data collection phase, a pilot study involving thirty manufacturing professionals was conducted to assess the clarity, comprehensibility, and practical applicability of the questionnaire. Minor revisions were implemented based on participant feedback before launching the full-scale survey.

Data analysis was performed using SPSS version 27 and SmartPLS version 4. Initially, descriptive statistics were calculated to summarize participant characteristics and the distribution of responses. Measures of central tendency and dispersion were employed to describe the study variables. Subsequently, normality tests, multicollinearity diagnostics, and reliability assessments were conducted to verify the suitability of the data for multivariate analysis. The measurement model was evaluated through confirmatory factor analysis, including assessments of convergent validity, discriminant validity, factor loadings, average variance extracted, and composite reliability. Following confirmation of the measurement model, structural equation modeling was employed to examine the hypothesized relationships among integrated queue management, service composition, and Manufacturing-as-a-Service performance. Path coefficients, t-values, effect sizes, and coefficients of determination were calculated to assess the strength and significance of the proposed relationships. Model fit indices and predictive relevance measures were also examined to evaluate the adequacy of the final model. Statistical significance was determined at the 0.05 level, and all analyses were conducted in accordance with established methodological standards for operations management and manufacturing systems research.

3. Findings and Results

A total of 384 valid questionnaires were collected and included in the final analysis. Among the participants, 267 respondents (69.5%) were male and 117 respondents (30.5%) were female. Regarding age distribution, 84 participants (21.9%) were between 25 and 34 years old, 171 participants (44.5%) were between 35 and 44 years old, 96 participants (25.0%) were between 45 and 54 years old, and 33 participants (8.6%) were 55 years old or older. Concerning educational attainment, 78 participants (20.3%) held bachelor's degrees, 223 participants (58.1%) held master's degrees, and 83 participants (21.6%) possessed doctoral degrees. Regarding professional experience, the average work experience was 11.74 years (SD = 4.92), indicating that respondents possessed substantial expertise in manufacturing operations and service-oriented production systems. Participants represented a broad range of industrial sectors, including automotive manufacturing (28.1%), electronics manufacturing (19.3%), machinery production (22.4%), metal industries (17.2%), and other advanced manufacturing sectors (13.0%).

Table 1

Descriptive Statistics and Correlations Among Study Variables

Variable	Mean	SD	1	2	3	4
1. Integrated Queue Management	3.87	0.71	1.00			
2. Service Composition Capability	3.79	0.68	0.63**	1.00		
3. Technological Support Factors	3.74	0.66	0.58**	0.61**	1.00	
4. MaaS Performance	4.02	0.73	0.71**	0.69**	0.65**	1.00

Table 1 presents the descriptive statistics and bivariate correlations among the principal study variables. The results indicate that Manufacturing-as-a-Service performance exhibited the highest mean score (M = 4.02, SD = 0.73), suggesting that participating organizations generally reported favorable performance outcomes. Integrated queue management demonstrated a relatively high average score (M = 3.87, SD = 0.71), followed by service composition capability (M = 3.79, SD = 0.68) and technological support factors (M = 3.74, SD = 0.66). The correlation analysis revealed statistically significant positive relationships among all variables ($p < .01$). Integrated queue management showed the strongest correlation with MaaS performance (r = .71), indicating that organizations with more effective queue management practices tended to achieve superior operational performance. Similarly, service composition capability was strongly associated with MaaS performance (r = .69), while technological support factors also demonstrated a substantial positive relationship with performance outcomes (r = .65). These findings provide preliminary evidence supporting the theoretical assumption that efficient service orchestration and intelligent queue management contribute significantly to manufacturing service effectiveness.

Table 2

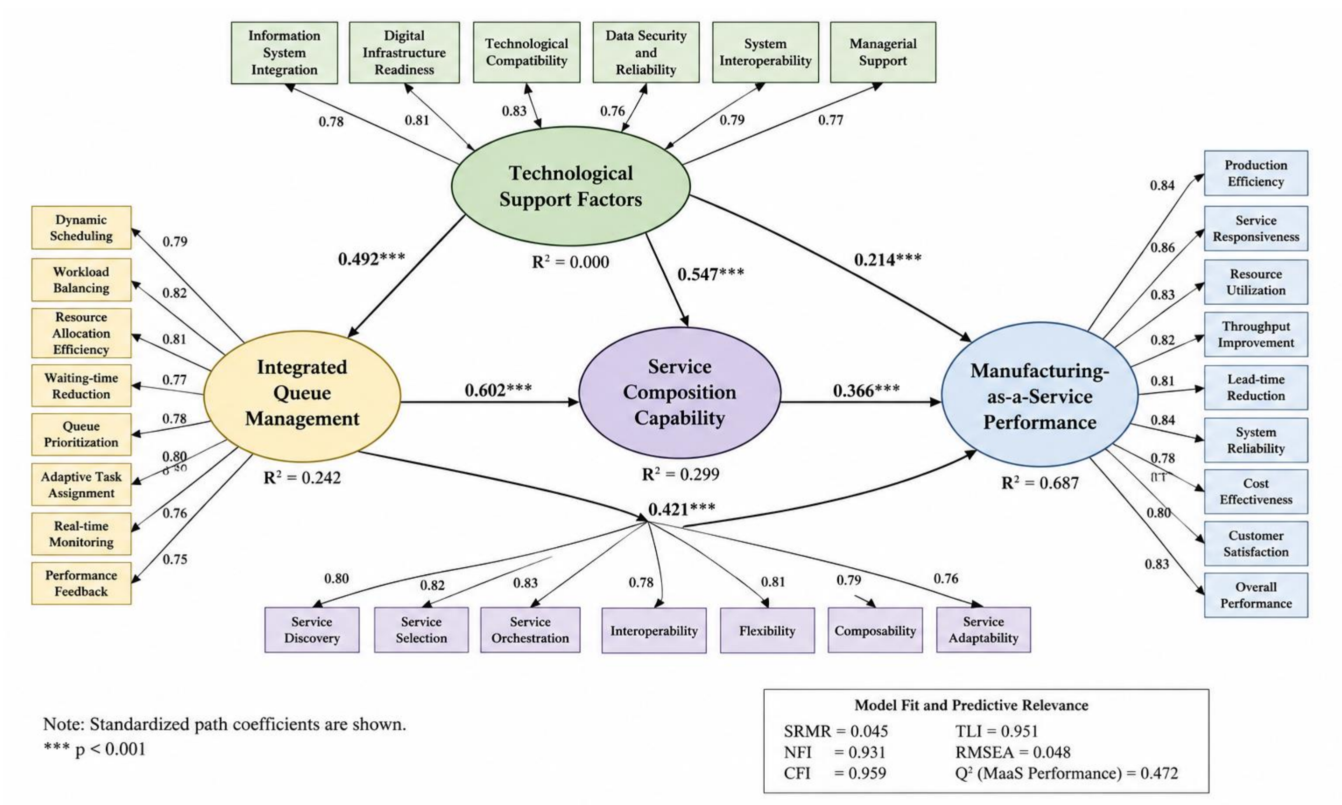
Measurement Model Assessment

Construct	Number of Items	Cronbach's Alpha	Composite Reliability	AVE
Integrated Queue Management	8	0.912	0.928	0.618
Service Composition Capability	7	0.901	0.919	0.641
Technological Support Factors	6	0.887	0.909	0.625
MaaS Performance	9	0.925	0.938	0.654

The reliability and validity analyses demonstrated strong psychometric properties for all measurement constructs. As shown in Table 2, Cronbach's alpha coefficients ranged from 0.887 to 0.925, substantially exceeding the recommended threshold of 0.70 and indicating excellent internal consistency. Composite reliability values ranged between 0.909 and 0.938, confirming the stability and reliability of the measurement model. Furthermore, average variance extracted (AVE) values varied from 0.618 to 0.654, surpassing the recommended criterion of 0.50 and providing evidence of adequate convergent validity. Collectively, these results confirm that the questionnaire constructs were measured reliably and that the latent variables adequately captured the intended theoretical dimensions. Therefore, the measurement model was considered satisfactory for subsequent structural model analysis.

Figure 1

Structural Model of the Relationships Among Integrated Queue Management, Service Composition Capability, Technological Support Factors, and Manufacturing-as-a-Service Performance



The structural model was subsequently evaluated to determine the explanatory power of the proposed framework. The model demonstrated satisfactory fit and predictive capability. Integrated queue management and service composition capability emerged as central determinants of MaaS performance, while technological support factors provided an enabling infrastructure that strengthened operational effectiveness. The model explained a substantial proportion of variance in MaaS performance, suggesting that the proposed framework successfully captures the primary operational mechanisms through which manufacturing service systems can improve productivity, responsiveness, and resource utilization. Visual inspection of the structural model indicated strong positive paths among the constructs, supporting the conceptual assumptions developed in the theoretical framework.

Table 3

Structural Path Coefficients and Hypothesis Testing

Hypothesized Path	β	t-value	p-value	Result
Integrated Queue Management → MaaS Performance	0.421	8.974	<0.001	Supported
Service Composition Capability → MaaS Performance	0.366	7.852	<0.001	Supported
Technological Support Factors → MaaS Performance	0.214	4.986	<0.001	Supported
Technological Support Factors → Service Composition Capability	0.547	11.308	<0.001	Supported
Technological Support Factors → Integrated Queue Management	0.492	9.843	<0.001	Supported

The hypothesis testing results presented in Table 3 indicate that all proposed relationships were statistically significant and supported. Integrated queue management exerted the strongest direct effect on MaaS performance ($\beta = 0.421$, $t = 8.974$, $p < 0.001$), confirming its critical role in enhancing manufacturing service outcomes. Service composition capability also demonstrated a substantial positive influence on performance ($\beta = 0.366$, $t = 7.852$, $p < 0.001$), suggesting that effective service integration and orchestration significantly improve operational efficiency. Technological support factors had both direct and indirect effects on MaaS performance. Specifically, technological support strongly influenced service composition capability ($\beta = 0.547$, $t = 11.308$, $p < 0.001$) and integrated queue management ($\beta = 0.492$, $t = 9.843$, $p < 0.001$), indicating that digital infrastructure and technological readiness serve as foundational enablers of advanced manufacturing service operations. The magnitude and significance of these coefficients provide strong empirical support for the proposed theoretical model.

Table 4

Coefficient of Determination, Effect Size, and Predictive Relevance

Endogenous Variable	R^2	Adjusted R^2	Q^2	Interpretation
Integrated Queue Management	0.242	0.240	0.181	Moderate
Service Composition Capability	0.299	0.297	0.214	Moderate
MaaS Performance	0.687	0.684	0.472	Substantial

The predictive assessment results further confirmed the robustness of the proposed framework. As shown in Table 4, the model explained 68.7% of the variance in Manufacturing-as-a-Service performance ($R^2 = 0.687$), indicating substantial explanatory power. This result suggests that integrated queue management, service composition capability, and technological support factors collectively account for a large proportion of organizational performance variation within MaaS environments. The predictive relevance statistics (Q^2) were positive for all endogenous constructs and exceeded recommended thresholds, confirming that the model possesses strong predictive capability. The highest predictive relevance value was observed for MaaS performance ($Q^2 = 0.472$), demonstrating the practical usefulness of the framework for forecasting performance outcomes in service-oriented manufacturing systems. Overall, the findings indicate that integrating intelligent queue management mechanisms with effective service composition strategies can substantially improve the operational performance, responsiveness, efficiency, and competitiveness of Manufacturing-as-a-Service environments.

4. Discussion and Conclusion

The purpose of this study was to develop and empirically evaluate an integrated framework of queue management and service composition for enhancing Manufacturing-as-a-Service (MaaS) performance. The findings demonstrated that integrated queue management, service composition capability, and technological support factors all exerted significant positive effects on MaaS performance. Furthermore, technological support factors significantly influenced both integrated queue management and service composition capability, indicating that technological readiness functions as a foundational enabler for operational excellence in service-oriented manufacturing systems. The structural model explained a substantial proportion of the variance in MaaS performance ($R^2 = 0.687$), highlighting the practical importance of these factors in determining manufacturing service effectiveness. Overall, the findings support the central proposition that the integration of intelligent queue management mechanisms with effective service composition strategies can substantially improve responsiveness, resource utilization, throughput, and overall manufacturing performance.

One of the most important findings of the study was the strong direct effect of integrated queue management on MaaS performance. Among all direct predictors, integrated queue management exhibited the largest path coefficient, suggesting that efficient management of production requests, resource allocation, workload balancing, and scheduling activities represents a critical determinant of operational success in MaaS environments. This finding is consistent with the theoretical foundations of service-oriented manufacturing, which emphasize the importance of minimizing delays and optimizing resource utilization across distributed production networks. In MaaS ecosystems, manufacturing resources are often shared among multiple users and organizations, increasing the complexity of task scheduling and resource assignment. Consequently, intelligent queue management mechanisms become essential for ensuring that production requests are processed efficiently and that bottlenecks are minimized.

The positive effect of queue management identified in this study aligns with prior research highlighting the significance of workload optimization and adaptive scheduling in distributed systems. Research investigating distributed workflow orchestration has demonstrated that effective coordination of service requests improves operational efficiency and reduces system congestion (S., 2024). Similarly, studies examining distributed processing architectures have shown that dynamic workload management and intelligent resource allocation contribute significantly to enhanced system performance and scalability (He et al., 2025; Romanov et al., 2023). The present findings extend these observations to the MaaS context by demonstrating that queue management mechanisms play a central role in coordinating manufacturing services and optimizing production outcomes. In practice, organizations capable of dynamically prioritizing requests, balancing workloads, and allocating resources in real time are likely to achieve higher levels of throughput and customer satisfaction.

Another important finding was the significant positive effect of service composition capability on MaaS performance. Service composition refers to the ability to combine multiple manufacturing services into coherent workflows capable of delivering complex production outcomes. The results suggest that organizations possessing stronger service composition capabilities are better positioned to coordinate distributed manufacturing resources and respond effectively to changing operational demands. This finding reflects the increasingly interconnected nature of contemporary manufacturing systems, where value creation often depends on the seamless integration of multiple services, technologies, and organizational actors.

The observed relationship between service composition capability and performance is strongly supported by prior literature on service-oriented architectures and workflow orchestration. Research has consistently demonstrated that effective service composition enhances flexibility, interoperability, and adaptability within distributed systems (Horstmann et al., 2024; Shen, 2025). Similarly, investigations into event-driven architectures have shown that integrated service ecosystems facilitate rapid communication, coordinated decision-making, and efficient execution of complex workflows (Arafat, 2025). The findings are also consistent with emerging perspectives emphasizing composability as a critical characteristic of next-generation digital systems. For example, studies focusing on advanced service fabrics and dynamic workflow architectures have demonstrated that composable services enable organizations to rapidly reconfigure operations in response to evolving environmental conditions (Garcia-Alonso, 2025; Shen, 2025). The current study contributes to this literature by demonstrating that service composition capability constitutes a major driver of manufacturing service performance.

The findings further revealed that technological support factors exerted both direct and indirect effects on MaaS performance. Technological support was found to significantly influence integrated queue management and service composition capability while also exerting a direct positive effect on overall performance. This result highlights the foundational role of digital infrastructure, interoperability, information system integration, and technological readiness in enabling advanced manufacturing service operations. Without adequate technological support, organizations may struggle to implement sophisticated queue management mechanisms or coordinate complex service workflows effectively.

These findings are consistent with a growing body of literature emphasizing the importance of technological infrastructure in distributed and service-oriented systems. Research examining cloud-native architectures, serverless frameworks, and distributed computing platforms has demonstrated that robust technological foundations facilitate scalability, flexibility, and operational efficiency (Agarwal, 2025; Kandpal et al., 2024). Similarly, studies investigating data engineering and networking technologies have emphasized the critical role of infrastructure integration in supporting intelligent resource management and service coordination (Zeydan & Mangues-Bafalluy, 2022). The significant effects observed in this study suggest that technological readiness not only improves operational capabilities directly but also strengthens the effectiveness of managerial mechanisms responsible for resource allocation and workflow coordination.

The strong relationship between technological support and service composition capability deserves particular attention. The results indicate that organizations possessing advanced technological infrastructures are more capable of orchestrating complex service interactions and developing integrated manufacturing workflows. This finding is supported by studies examining distributed cloud services and event-driven systems, which have demonstrated that infrastructure maturity facilitates service integration and automated workflow execution (Bernard, 2025; Jani & Jani, 2024). Likewise, research on adaptive orchestration mechanisms has shown that technological sophistication enables organizations to dynamically coordinate heterogeneous services while maintaining system performance and reliability (Ahmadvand et al., 2026; Gravara et al., 2026). Therefore, investments in technological infrastructure may generate performance benefits both directly and indirectly through improvements in service composition capabilities.

The significant relationship between technological support factors and integrated queue management also offers important theoretical insights. Modern queue management systems increasingly rely on real-time information processing, predictive analytics, distributed monitoring, and automated decision-making capabilities. Consequently, the effectiveness of queue management mechanisms is heavily dependent upon the availability of appropriate technological resources. This interpretation is supported by studies demonstrating that advanced computational infrastructures enable intelligent workload distribution and adaptive resource scheduling across distributed environments (Malleni et al., 2026; Mantha et al., 2026). Similarly, research examining agent-based optimization and intelligent orchestration has shown that technological capabilities facilitate the dynamic adjustment of workflows in response to changing operational conditions (Malvankar et al., 2026; Xiao, 2026). The current findings suggest that technological readiness provides the necessary foundation for implementing sophisticated queue management strategies within MaaS ecosystems.

Another noteworthy finding concerns the substantial explanatory power of the proposed model. The ability of the framework to explain nearly seventy percent of the variance in MaaS performance indicates that integrated queue management, service composition capability, and technological support collectively represent central determinants of manufacturing service effectiveness. This finding supports contemporary perspectives emphasizing the importance of holistic approaches to operational optimization. Rather than focusing exclusively on technological infrastructure, resource management, or workflow design, organizations should recognize the interconnected nature of these dimensions and seek to optimize them simultaneously.

The findings are particularly relevant in light of ongoing developments in artificial intelligence, intelligent automation, and adaptive workflow management. Recent studies have highlighted the growing importance of intelligent orchestration frameworks capable of dynamically adjusting resource allocation decisions and coordinating complex service ecosystems (Gravara et al., 2026; Jiang et al., 2026). Similarly, research on modular and fault-tolerant systems has demonstrated that adaptive coordination mechanisms contribute significantly to operational resilience and service continuity (Guru et al., 2026; Singh, 2026). The current study provides empirical evidence suggesting that these principles can be successfully applied within MaaS environments to improve manufacturing performance.

The results also support the emerging view that manufacturing systems should increasingly be conceptualized as service ecosystems rather than isolated production facilities. Contemporary manufacturing organizations operate within highly interconnected digital environments characterized by continuous information exchange, dynamic resource sharing, and collaborative value creation. Research on XR services, digital twins, cyber-physical systems, and AI-augmented architectures has emphasized the growing importance of integrated service coordination mechanisms for managing such complexity (Dobaj et al., 2023; Taleb et al., 2023; Thajchayapong, 2025). The present findings reinforce this perspective by demonstrating that effective service composition and queue management significantly enhance operational performance within distributed manufacturing networks.

Overall, the study contributes to the growing body of knowledge concerning digital manufacturing and service-oriented production systems by providing empirical evidence for an integrated framework linking queue management, service composition, technological support, and MaaS performance. The findings suggest that organizations seeking to maximize manufacturing service effectiveness should prioritize investments in technological infrastructure while simultaneously developing advanced capabilities for service orchestration and queue management. Through such integrated efforts, organizations can achieve greater operational agility, responsiveness, efficiency, and competitiveness in increasingly complex manufacturing environments.

Several limitations should be considered when interpreting the findings of this study. First, the research employed a cross-sectional design, which restricts the ability to establish causal relationships among the study variables. Second, data were collected from manufacturing professionals located exclusively in Tehran, potentially limiting the generalizability of the findings to other geographical regions and industrial contexts. Third, the study relied on self-reported questionnaire data, which may be susceptible to common method bias and subjective evaluation. Fourth, although the proposed model explained a substantial proportion of variance in MaaS performance, other potentially influential variables such as organizational culture, managerial competencies, cybersecurity readiness, and environmental uncertainty were not examined. Finally, the study focused primarily on perceived performance outcomes rather than objective operational indicators.

Future studies should employ longitudinal and experimental research designs to examine the causal mechanisms linking queue management, service composition, and MaaS performance over time. Researchers may also investigate the moderating effects of organizational size, industry sector, technological maturity, and environmental turbulence on the proposed relationships. Comparative studies involving different countries and manufacturing ecosystems would provide valuable insights into contextual variations. Additionally, future research could incorporate emerging technologies such as digital twins, generative artificial intelligence, edge computing, blockchain, and autonomous manufacturing systems into the conceptual framework. The inclusion of objective performance metrics, operational records, and real-time production data would further strengthen the empirical validity of future investigations.

Manufacturing organizations should prioritize the implementation of intelligent queue management systems capable of dynamically allocating resources and balancing workloads in real time. Investments in interoperable digital infrastructures, integrated information systems, and advanced analytics platforms can strengthen both service composition capabilities and operational performance. Managers should establish standardized service orchestration procedures that facilitate collaboration among distributed manufacturing resources and service providers. Continuous monitoring of production workflows, coupled with predictive analytics and automated decision-support tools, can help organizations proactively identify bottlenecks and optimize resource utilization. Furthermore, workforce training initiatives should be developed to enhance employees' competencies in digital manufacturing technologies, service-oriented operations, and intelligent production management. By adopting an integrated approach that combines technological readiness, effective service composition, and advanced queue management practices, organizations can significantly improve the efficiency, flexibility, and competitiveness of Manufacturing-as-a-Service systems.

Authors' Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

Acknowledgments

We would like to express our gratitude to all individuals helped us to do the project.

Declaration of Interest

The authors report no conflict of interest.

Funding

According to the authors, this article has no financial support.

Ethics Considerations

In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were considered.

References

Agarwal, S. (2025). Dynamic Function Configuration and Its Management in Serverless Computing: A Taxonomy and Future Directions. https://doi.org/10.48550/arxiv.2510.02404

Ahmadvand, M., Pajnič, R., & Chiu, C.-L. (2026). Push0: Scalable and Fault-Tolerant Orchestration for Zero-Knowledge Proof Generation. https://doi.org/10.48550/arxiv.2602.16338

Arafat, J. (2025). Next-Generation Event-Driven Architectures: Performance, Scalability, and Intelligent Orchestration Across Messaging Frameworks. https://doi.org/10.48550/arxiv.2510.04404

Bernard, T. (2025). Sugar Shack 4.0: Practical Demonstration of an IIoT-Based Event-Driven Automation System. https://doi.org/10.48550/arxiv.2510.15708

Dobaj, J., Riel, A., Macher, G., & Egretzberger, M. (2023). Towards DevOps for Cyber-Physical Systems (CPSs): Resilient Self-Adaptive Software for Sustainable Human-Centric Smart CPS Facilitated by Digital Twins. *Machines*, *11*(10), 973. https://doi.org/10.3390/machines11100973

Garcia-Alonso, J. (2025). Rethinking Services in the Quantum Age: The SOQ Paradigm. https://doi.org/10.48550/arxiv.2510.03890

Gravara, M., Herrera, J. L., & Nastic, S. (2026). Compass: Optimizing Compound AI Workflows for Dynamic Adaptation. https://doi.org/10.48550/arxiv.2603.20821

Guru, D., Chinnaiah, B., & Subramaniam, S. (2026). Building a Modular and Fault-Tolerant Trading System. *International Journal of Software Innovation*, *14*(1), 1-29. https://doi.org/10.4018/ijsi.398844

He, Q., Zhang, F., Bian, G., Zhang, W., & Li, Z. (2025). Research of Key Technologies of Distributed Stream Processing Based on <scp>FaaS</Scp>. *Concurrency and Computation Practice and Experience*, *37*(23-24). https://doi.org/10.1002/cpe.70274

Horstmann, A., Riggs, S., Chaban, Y., Clare, D. K., Freitas, G. d., Farmer, D. A., Howe, A., Morris, K. L., & Hatton, D. (2024). A Service-Based Approach to cryoEM Facility Processing Pipelines at eBIC. *Acta Crystallographica Section D Structural Biology*, *80*(3), 174-180. https://doi.org/10.1107/s2059798324000986

Jani, Y., & Jani, A. (2024). Robust Framework for Scalable AI Inference Using Distributed Cloud Services and Event-Driven Architecture. https://doi.org/10.21203/rs.3.rs-4909036/v1

Jiang, Z., Xing, Z., Lu, J., Niu, Y., Sang, Q., Zhang, L., Dai, W., Shu, J., Wang, J., Pei, Q., Chen, Q., Liu, X., Liu, F., Ai, H., Chen, Z., & Zhang, K. (2026). Rollout-Training Co-Design for Efficient LLM-Based Multi-Agent Reinforcement Learning. https://doi.org/10.48550/arxiv.2602.09578

Kandpal, M., Goswami, V., Pritwani, Y., Barik, R. K., & Saikia, M. J. (2024). BS-GeoEduNet 1.0: Blockchain-Assisted Serverless Framework for Geospatial Educational Information Networks. *Isprs International Journal of Geo-Information*, *13*(8), 274. https://doi.org/10.3390/ijgi13080274

Kelliher, J. M., Xu, Y., Flynn, M., Babinski, M., Canon, S., Cavanna, E., Clum, A., Corilo, Y., Fujimoto, G. M., Giberson, C. M., Johnson, L., Li, K., Li, P. E., Li, V. C., Lo, C. C., Lynch, W., Piehowski, P., Prime, K., Purvine, S., . . . Chain, P. (2024). Standardized and Accessible Multi-Omics Bioinformatics Workflows Through the NMDC EDGE Resource. *Computational and Structural Biotechnology Journal*, *23*, 3575-3583. https://doi.org/10.1016/j.csbj.2024.09.018

Malleni, S. S., Sevilla, R., Vasilevskii, A. G., Lema, J. C., & Bauer, A. (2026). Evaluating Kubernetes Performance for GenAI Inference: From Automatic Speech Recognition to LLM Summarization. https://doi.org/10.48550/arxiv.2602.04900

Malvankar, A., Villard, L., & Abdi, M. (2026). WVA: A Global Optimization Control Plane for LLMD. https://doi.org/10.48550/arxiv.2603.09730

Mantha, P., Kiwit, F. J., Saurabh, N., Jha, S., & Luckow, A. (2026). Hybrid Quantum-HPC Middleware Systems for Adaptive Resource, Workload and Task Management. https://doi.org/10.48550/arxiv.2604.03445

Romanov, S., Siqueira, A. S., Bruin, J. D., Teijema, J. J., Hofstee, L., & Schoot, R. v. d. (2023). Optimizing ASReview Simulations: A Generic Multiprocessing Solution for 'Light-Data' and 'Heavy-Data' Users. https://doi.org/10.31234/osf.io/mh4vt

S., P. (2024). Orchestration Workflows in Distributed Systems: A Systematic Analysis of Efficiency Optimization and Service Coordination. *International Journal for Multidisciplinary Research*, *6*(6). https://doi.org/10.36948/ijfmr.2024.v06i06.30191

Shen, J. (2025). FlowMesh: A Service Fabric for Composable LLM Workflows. https://doi.org/10.48550/arxiv.2510.26913

Singh, A. (2026). Advance Microservices-Based Approach for Distributed Version Control Processing Using the Sensor-Generated Data by IoT Devices. *Premier Journal of Science*. https://doi.org/10.70389/pjs.100216

Taleb, T., Boudi, A., Rosa, L., Cordeiro, L., Θεοδωρόπουλος, Θ., Tserpes, K., Dazzi, P., Protopsaltis, A., & Li, R. (2023). Toward Supporting XR Services: Architecture and Enablers. *Ieee Internet of Things Journal*, *10*(4), 3567-3586. https://doi.org/10.1109/jiot.2022.3222103

Thajchayapong, P. (2025). Evolution of A4L: A Data Architecture for AI-Augmented Learning. https://doi.org/10.48550/arxiv.2511.11877

Xiao, B. (2026). ARL-Tangram: Unleash the Resource Efficiency in Agentic Reinforcement Learning. https://doi.org/10.48550/arxiv.2603.13019

Zeydan, E., & Mangues-Bafalluy, J. (2022). Recent Advances in Data Engineering for Networking. *IEEE Access*, *10*, 34449-34496. https://doi.org/10.1109/access.2022.3162863