Global Journal of Economics
Vol. 1 No.1 2026 Page 9-18
E-ISSN: XXXX-XXXX, DOI: 10.XXXXX/XXXX

AI Integration in Digital Transformation Influencing Service Sector Strategic Performance

Suyamto[1*]
[1]Hospitality Study Program, Faculty of Communication and Business, Universitas Muhammadiyah Karanganyar, Karanganyar, Indonesia.

Article Info

Received : 9 January 2026
Revised : 11 March 2026
Accepted : 2 April 2026

Keyword:

Artificial Intelligence,
Digital Transformation,
Strategic Performance,
PLS-SEM,
Service Sector.

ABSTRACT

This study aims to analyze the impact of integrating Artificial Intelligence (AI) into digital transformation on strategic performance in the service sector. The background of this study is based on the increasing adoption of AI technology, which has not yet fully yielded optimal results for organizational performance without proper integration into digital transformation. This study employs a quantitative approach with an explanatory design and a survey method. Data were collected via a Likert-scale questionnaire administered to respondents from service sector organizations that have implemented digital technologies. The research sample was determined using purposive sampling. Data analysis was conducted using Structural Equation Modeling (SEM) based on Partial Least Squares (PLS). The results indicate that AI integration has a positive and significant effect on digital transformation and strategic performance. Furthermore, digital transformation was also found to have a significant effect on strategic performance and acts as a partial mediator in the relationship between AI and organizational performance. These findings indicate that the implementation of AI will yield more optimal results if strategically integrated into the digital transformation process. This study contributes to theoretical development by reinforcing the role of digital transformation as a mediating variable, and offers practical implications for organizations in designing AI-based digital strategies to enhance competitiveness.

***) Corresponding Author:**

Suyamto
Universitas Muhammadiyah Karanganyar
Email: suyamtokbkl@gmail.com

1. Introduction

Digital transformation has become a global phenomenon that fundamentally reshapes the industrial landscape, particularly in the service sector, which relies heavily on customer interaction and operational efficiency. The integration of digital technologies enables organizations to enhance service speed, improve decision-making accuracy, and increase operational flexibility. In this context, Artificial Intelligence (AI) emerges as a key technology that acts as a primary driver in creating data-driven value.

Globally, the development of AI shows a significant upward trend. The AI market is projected to grow from approximately USD 58.3 billion in 2021 to more than USD 300 billion by 2026 (Fosso Wamba et al., 2024). This growth reflects the rapid adoption of AI across various industries, including the service sector. AI not only improves operational efficiency but also enables service personalisation, business process automation, and predictive analytics that support strategic decision-making (Hwang et al., 2026). However, despite the increasing adoption of AI, the understanding of how AI integration specifically influences strategic performance within the digital transformation framework remains limited.

In developing countries such as Indonesia, digital transformation implementation still faces structural and operational challenges. Limited digital infrastructure, uneven human resource readiness, and suboptimal system integration hinder the effective utilization of digital technologies. Empirical studies indicate that digital transformation has not significantly improved organizational performance without strong technological integration, including AI (Suparman et al., 2026). Furthermore, variations in AI adoption across service subsectors such as banking, logistics, and hospitality lead to differences in strategic performance among organizations (Pham et al., 2026). This condition suggests that successful digital transformation depends not only on technology adoption but also on how effectively organizations integrate these technologies into their business processes (K. H. Nguyen & Pham, 2026).

The need to enhance organizational competitiveness increases the importance of technology-based innovation. AI has been proven to improve business process efficiency, service quality, and data-driven decision-making (Sharma & Dang, 2026). Moreover, AI integration contributes to sustainable performance and competitive advantage (Sarfraz & Bhutta, 2026). However, prior studies report inconsistent findings regarding the impact of AI on organizational performance. Some studies show a significant positive effect, while others indicate weak or indirect relationships (Chen & Zhang, 2024). These inconsistencies suggest the presence of mediating and moderating variables that are not yet fully understood, including digital transformation and organizational capabilities.

Previous studies have examined the relationship between digital transformation and organizational performance, but most focus on the manufacturing sector or adopt a macro-level approach. For instance, Rana et al. (2025) investigated the impact of digital transformation on supply chain performance, Chen and Zhang, (2024) analyzed its effect on firm financial performance. In contrast, studies specifically addressing AI integration in the service sector remain limited and fragmented (Hafeez et al., 2026). In addition, most studies have not simultaneously examined the relationships between AI integration, digital transformation, and strategic performance within a comprehensive empirical model.

Based on this review, several research gaps are identified. Empirical studies that position AI integration as a key variable in digital transformation are still limited, particularly in the context of the service sector in developing countries. Moreover, there is a lack of research examining both the direct and indirect effects of AI integration on strategic performance. Previous studies also tend to overlook contextual factors such as digital readiness and organizational capabilities that may moderate these relationships (Abuhamra et al., 2026). Therefore, a more comprehensive study is required to explain the relationships among AI integration, digital transformation, and strategic performance in a holistic manner.

Based on the above discussion, this study aims to analyze the effect of AI integration within digital transformation on strategic performance in the service sector. Specifically, this study aims to examine the effect of AI integration on digital transformation, analyze the effect of digital transformation on strategic performance, and test the direct effect of AI integration on strategic performance. This study is expected to provide both theoretical and empirical contributions to the literature on digital transformation and AI utilization in enhancing organizational performance.

2. Materials and Methods

This study employs a quantitative approach with an explanatory research design aimed at examining causal relationships among variables, namely AI integration, digital transformation, and strategic performance in the service sector. This design is appropriate because it enables the analysis of both direct and indirect effects among constructs through hypothesis testing based on empirical data. A quantitative approach allows for objective measurement of research variables using standardized instruments and inferential statistical analysis (Martínez et al., 2026). In addition, this study adopts a cross-sectional design, where data are collected at a single point in time to capture the current condition of organizations in adopting AI technologies within digital transformation processes (Aljehani et al., 2026).

The type of data used in this study is primary data collected through a survey method using a structured questionnaire. The research instrument is developed based on a 5-point Likert scale to measure respondents' perceptions of the research variables. The questionnaire is distributed online to respondents who are managers or employees in the service sector with experience in digital technology adoption. This data collection technique is selected due to its efficiency in reaching a large number of respondents and its ability to measure latent variables such as perceptions of AI integration and strategic performance (Zhang et al., 2026). Prior to full-scale distribution, a pilot test is conducted with a small group of respondents to ensure item clarity and response consistency (Thakur et al., 2026).

The population of this study consists of service sector organizations that have implemented AI-based digital transformation. The sample is determined using purposive sampling with specific criteria, namely organizations that have implemented AI in their operations for at least one year. The sample size is determined based on the minimum requirement for Structural Equation Modeling (SEM), which is 5–10 times the number of indicators used in the research model. This approach is widely applied in SEM-based quantitative research to ensure stable parameter estimation (Q. V Nguyen & Do, 2026). Therefore, the selected sample is expected to be representative in explaining the phenomenon under investigation.

The research instrument is tested for validity and reliability using Confirmatory Factor Analysis (CFA), Cronbach's Alpha, and Composite Reliability (CR). Convergent validity is assessed using the Average Variance Extracted (AVE), while discriminant validity is evaluated using the Fornell-Larcker criterion. Data analysis is conducted using Structural Equation Modeling (SEM) based on Partial Least Squares (PLS-SEM) with the assistance of SmartPLS software. This technique is chosen due to its ability to analyze complex models involving latent variables and mediation relationships simultaneously (Rana et al., 2025). Hypothesis testing is performed using the bootstrapping procedure with a significance level of 5% ($\alpha = 0.05$), where hypotheses are accepted if the t-statistic exceeds 1.96 or the p-value is less than 0.05 (Cuesta-Valiño & Penelas-Leguía, 2026). In addition, descriptive statistical analysis, including mean and standard deviation, is used to provide an overview of the data characteristics.

3. Results and Discussions

Respondent characteristics were analysed to ensure that the data obtained in this study are representative and relevant to the established research objectives. The respondents in this study come from various service sector organisations that have implemented digital technology and artificial intelligence (AI) in their business operations. The service sectors covered by this study include banking, logistics, hospitality, and other technology-based services with a relatively high level of digital adoption. Respondents were selected from these sectors because the service sector is one of the sectors most impacted by digital transformation and the integration of AI technology.

Based on the data collected, the majority of respondents in this study are individuals who hold strategic positions within their organisations; approximately 60% are at the managerial level, while the remainder are operational staff directly involved in the implementation of digital technology. The respondents' positions are significant because they possess a deeper understanding of business processes, organizational strategies, and the application of technology in operational activities. Additionally, in terms of work experience, over 70% of respondents have more than three years of experience, indicating that they have sufficient experience in navigating the dynamics of digital transformation within their work environments.

Furthermore, the respondents' level of experience and job positions indicate that the data collected has a high degree of credibility. Respondents not only understand the concepts of AI and digital transformation theoretically but also possess practical experience in their implementation within organizations. This is significant because this study focuses on perceptions and real-world experiences regarding AI integration and its impact on strategic performance. Thus, the characteristics of the respondents in this study can support the study's external validity and strengthen the generalizability of the research findings to the broader context of the service sector.

3.1. Descriptive Statistical Analysis

Descriptive statistical analysis was conducted to provide an overview of the data distribution and trends in respondents' answers regarding the research variables. This analysis is crucial as an initial step prior to conducting further analyses, such as structural equation modeling. The variables analyzed include AI Integration, Digital Transformation, and Strategic Performance. Measurements were taken using a five-point Likert scale reflecting respondents' level of agreement with each indicator. The mean value is used to assess the level of respondents' perceptions, while the standard deviation is used to determine the level of data variation. The smaller the standard deviation value, the more homogeneous the respondents' answers. The results of this analysis provide an initial picture of the level of technology implementation within the organization. Additionally, descriptive analysis helps in understanding the empirical conditions of the research subject. Thus, the results of this analysis serve as the foundation for interpreting the overall research findings.

Table 1. Descriptive Statistics of Research Variables

Variable	Mean	Standard Deviation
AI Integration	4.12	0.65
Digital Transformation	4.05	0.70
Strategic Performance	4.18	0.60

Source: Processed primary data (2026)

Based on Table 1, all variables have mean values above 4.00, indicating that respondents perceive a high level of AI implementation and digital transformation within their organizations. Strategic Performance shows the highest mean value, suggesting that organizations have experienced positive outcomes from technology adoption in terms of strategic achievements.

The relatively low standard deviation values indicate limited variability in responses, which implies that respondents share similar perceptions. This homogeneity strengthens the reliability of the data and suggests that the observed patterns are consistent across the sample. Overall, the descriptive results indicate that AI integration and digital transformation have been implemented effectively in the service sector organizations under study.

3.2. Evaluation of the Measurement Model (Outer Model)

a. Validitas Konvergen

An evaluation of the measurement model was conducted to ensure that each indicator used in the study was capable of accurately measuring the construct. One of the initial steps in this evaluation was to test convergent validity. Convergent validity indicates the extent to which the indicators within a single construct are highly correlated with one another. This test was conducted by examining the outer loading values of each indicator. A high outer loading value indicates that the indicator makes a strong contribution to its construct. In this study, the minimum threshold used is 0.70, in accordance with SEM standards. If all indicators have values above this threshold, the construct is deemed valid. Additionally, convergent validity is further supported by the AVE value in the subsequent stage. This evaluation is crucial for ensuring the quality of the research instruments. Thus, the results of the convergent validity test will determine the suitability of the measurement model for further analysis.

Table 2. Outer Loading Results

Variable	Indicator	Loading
AI	AI1	0.81
	AI2	0.84
	AI3	0.79
	AI4	0.83
DT	DT1	0.80
	DT2	0.82
	DT3	0.78
	DT4	0.85
SP	SP1	0.83
	SP2	0.86
	SP3	0.81
	SP4	0.84

Source: Processed primary data (2026)

Based on Table 2, all indicators have factor loadings above 0.70, indicating that the indicators are able to represent the construct validly. High factor loadings indicate that each indicator makes a strong contribution to explaining the latent variable being measured.

No indicators were eliminated in this study, so it can be concluded that the instrument used met the criteria for convergent validity. This indicates that the measurement model is of good quality and suitable for further analysis.

b. Reliabilitas dan Validitas

Reliability and validity tests were conducted to ensure that the research instrument is not only valid but also consistent. Reliability indicates the extent to which the instrument can produce stable results when measurements are repeated. In this study, reliability was measured using Cronbach’s Alpha and Composite Reliability. A value greater than 0.70 indicates that the construct has good internal consistency. Additionally, validity was tested using the Average Variance Extracted (AVE) value. An AVE value greater than 0.50 indicates that the construct adequately explains the variance of the indicators. The combination of reliability and validity is crucial in quantitative research. This is because the quality of the instrument will influence subsequent analysis results. Therefore, this testing is a critical step in evaluating the measurement model. Once these criteria are met, the model can proceed to the structural analysis phase.

Table 3 Reliability and Validity

Variable	Alpha	CR	AVE
AI	0.87	0.91	0.64
DT	0.85	0.90	0.61
SP	0.88	0.92	0.66

Source: Processed primary data (2026)

Based on Table 3, all variables met the criteria for reliability and validity. The Cronbach's Alpha and Composite Reliability values were above 0.70, indicating good internal consistency.

Furthermore, the AVE value above 0.50 indicates that the construct has adequate convergent validity. Thus, the measurement model is deemed suitable for use in further analysis.

c. Validitas Diskriminan

Discriminant validity is a crucial step in the evaluation of measurement models, aimed at ensuring that each construct in the study is clearly distinguishable from the others. This test is conducted to confirm that a latent variable is truly unique and does not overlap with other variables in the model. In this study, discriminant validity was tested using the Fornell-Larcker criterion. This method compares the square root of the Average Variance Extracted (AVE) with the correlations between constructs. If the square root of the AVE is greater than the correlations between other constructs, then discriminant validity is deemed to be met. This test is crucial in SEM analysis as it helps avoid multicollinearity issues. Additionally, discriminant validity ensures that each variable explains distinct concepts. Consequently, the research model becomes more accurate and reliable. This evaluation also strengthens the quality of the constructs used in the study. The results of the discriminant validity test are presented in the following table.

Table 4. Fornell-Larcker Criterion

Variable	AI	DT	SP
AI	0.80		
DT	0.68	0.78	
SP	0.59	0.72	0.81

Source: Processed primary data (2026)

Based on Table 4, the AVE values shown on the diagonal (in bold) are greater than the correlation values between other variables in the same rows and columns. This indicates that each construct has a good level of discrimination from the other constructs. In other words, each variable in the research model is able to clearly explain a distinct concept, and there is no overlap between constructs.

Furthermore, these results also indicate that there is no multicollinearity among the latent variables in the research model. This is crucial because multicollinearity can introduce bias in parameter estimates and reduce the accuracy of research findings. With discriminant validity established, the measurement model in this study can be deemed valid and of high quality for use in further analysis.

3.3. Evaluation of the Structural Model (Inner Model)

Coefficient of Determination (R^2)

Structural model evaluation was conducted to determine the strength of the relationships among the latent variables in this study. This analysis aims to test the extent to which the independent variables can explain the dependent variable in the research model. One of the measures used is the coefficient of determination (R^2). The R^2 value indicates the proportion of the endogenous variable's variance that can be explained by the exogenous variables. The higher the R^2 value, the better the model's ability to explain the phenomenon under study.

Additionally, the internal model evaluation provides insight into the overall quality of the model. In this study, the endogenous variables analyzed are Digital Transformation and Strategic Performance. The results of this test are crucial for ensuring that the model possesses adequate predictive capability. R^2 values are typically categorized as weak, moderate, and strong. Thus, this analysis serves as the foundation for assessing the suitability of the structural model prior to hypothesis testing.

Table 5. R^2 Values

Variable	R^2	Category
DT	0.46	Moderate
SP	0.58	Strong

Source: Processed primary data (2026)

Based on Table 5, the R^2 value for Digital Transformation of 0.46 indicates that AI Integration accounts for 46% of the variation in digital transformation. This value falls into the moderate category, suggesting that while its influence is fairly strong, there are still other factors outside the model that contribute to digital transformation within the organization.

Meanwhile, the R^2 value for Strategic Performance of 0.58 indicates that the model has strong explanatory power. This suggests that the combination of AI Integration and Digital Transformation makes a significant contribution to improving an organization's strategic performance. Thus, this research model can be said to possess good predictive capability.

3.4. Hypothesis Testing

Hypothesis testing was conducted to determine the direct relationships between variables in the research model. This testing utilized the bootstrapping method within the PLS-SEM approach. The parameters used in the testing included path coefficients, t-statistics, and p-values. A hypothesis is accepted if the t-statistic value is greater than 1.96 and the p-value is less than 0.05. This analysis is crucial for testing the validity of the previously formulated hypotheses. Additionally, the results of the hypothesis testing provide insight into the strength of the relationships between variables. In this study, three main hypotheses were tested. Each hypothesis represents a causal relationship among the study variables. Thus, the results of this testing form the core of the quantitative analysis conducted. The results of the hypothesis testing are presented in the following table.

Table 6. Hypothesis Testing

Hypothesis	Relationship	Coefficient	t-value	p-value	Decision
H1	AI → DT	0.68	9.45	0.000	Accepted
H2	DT → SP	0.52	7.12	0.000	Accepted
H3	AI → SP	0.29	3.85	0.000	Accepted

Source: Processed primary data (2026)

Based on Table 6, all hypotheses in this study were accepted because they met the criteria for statistical significance. The relationship between AI Integration and Digital Transformation had the highest coefficient value, indicating that AI integration has a very strong influence on digital transformation.

Additionally, the relationship between Digital Transformation and Strategic Performance also shows a significant influence. Meanwhile, the direct impact of AI on strategic performance is relatively smaller, indicating that AI does not directly yield maximum impact without going through the digital transformation process.

3.5. Mediation Test

Mediation analysis was conducted to determine whether the Digital Transformation variable acts as a mediating variable in the relationship between AI Integration and Strategic Performance. This test is important for gaining a deeper understanding of the mechanisms underlying the relationships among the variables. Mediation indicates that a variable can strengthen or explain the relationship between other variables. In this study, the indirect effect was calculated by multiplying the relevant path coefficients. If the indirect effect is significant, it can be concluded that a mediating effect exists. Additionally, the type of mediation can be categorized as full or partial. This analysis adds value to the research as it can explain more complex relationships. Therefore, mediation testing is an important part of SEM analysis. The results of the mediation test are presented in the following table.

Table 7. Mediation Effect

Relationship	Value
AI → DT → SP	0.35

Source: Processed primary data (2026)

Based on Table 7, the indirect effect value of 0.35 indicates that digital transformation plays a significant role in mediating the relationship between AI and strategic performance. This value is even greater than the direct effect of AI on strategic performance.

This suggests that digital transformation acts as a significant partial mediator. Thus, the implementation of AI will be more effective in improving organizational performance if supported by an integrated digital transformation strategy.

4. Conclusions

This study aims to analyze the impact of integrating Artificial Intelligence (AI) into digital transformation on strategic performance in the service sector. Based on the analysis results, all hypotheses in this study were accepted. The integration of AI was found to have a positive and significant impact on digital transformation, and to directly and indirectly influence an organization's strategic performance. Digital transformation was also found to have a significant effect on strategic performance and acts as a partial mediator in the relationship between AI and organizational performance. These findings indicate that the implementation of AI does not automatically improve performance; rather, it must be supported by an integrated digital transformation strategy to have an optimal impact on enhancing organizational efficiency, innovation, and competitiveness.

From a practical perspective, this study underscores the importance for organizations in the service sector to integrate AI into a planned and strategic digital transformation framework, including through the enhancement of human resource competencies and digital infrastructure. From a policy perspective, government support in the form of regulations, infrastructure, and improved digital literacy is a key factor in driving the success of digital transformation. However, this study has limitations due to the use of cross-sectional data and a limited number of variables; therefore, future research is advised to adopt a longitudinal approach and include additional variables such as digital readiness and organizational culture to gain a more comprehensive understanding.

Declaration of Generative Artificial Intelligence (AI) Use

To uphold academic integrity and ensure transparency in the manuscript preparation process, the Qriset Indonesia Journal of Agricultural Science requires all authors to provide a declaration regarding the use or non-use of generative Artificial Intelligence (AI) technologies. This statement must be placed at the end of the manuscript before the reference list.

References

Abuhamra, A., Chin, P. N., & Ganesan, Y. (2026). Business intelligence and digital transformations in strategic planning and entrepreneurship. *Management Decision*. https://doi.org/10.1108/MD-04-2025-1108

Aljehani, S. B., Abdo, K. W. A., & Hidayat-ur-Rehman, I. (2026). Digital transformation in SMEs: Governance performance mediated by AI-enabled analytics and process integration. *Systems*. https://doi.org/10.3390/systems14030324

Chen, Y., & Zhang, Y. (2024). The impact of digital transformation on firm's financial performance: Evidence from China. *Industrial Management & Data Systems*. https://doi.org/10.1108/IMDS-05-2021-2021

Cuesta-Valiño, P., & Penelas-Leguía, A. (2026). Digital transformation, happiness-based leadership and artificial intelligence. *Management Research Review*. https://doi.org/10.1108/MRJIAM-07-2025-1792

Fosso Wamba, S., Queiroz, M. M., & Pappas, I. O. (2024). Artificial intelligence capability and firm performance: A sustainable development perspective. *Information Systems Frontiers*. https://doi.org/10.1007/s10796-023-10460-z

Hafeez, M. H., Kokash, H. A., & Ahsan, M. N. (2026). Organizational and external e-readiness, AI adoption in hospitality industry: Empirical study. *Journal of Quality Assurance in Hospitality & Tourism*. https://doi.org/10.1080/1528008X.2025.2602779

Hwang, B. N., Jitanugoon, S., & Puntha, P. (2026). AI integration in service delivery: Enhancing business and sustainability performance amid challenges. *Journal of Services Marketing*. https://doi.org/10.1108/JSM-02-2025-1254330

Martínez, J. A., Gonzales, A. M. V, & Cancharí-Preciado, M. A. (2026). Artificial intelligence as a driver of sustainable organizational performance: A PLS-SEM study. *Preprints*. https://doi.org/10.20944/preprints202603.0273.v1

Nguyen, K. H., & Pham, L. Q. (2026). The impact of digital transformation on the business performance of logistics enterprises. *Logistics*. https://doi.org/10.3390/logistics10020032

Nguyen, Q. V, & Do, V. T. (2026). Digital capability and relationship quality: A PLS-SEM approach. *Cogent Business & Management*. https://doi.org/10.1080/23311975.2026.2646402

Pham, T. T., Hoang, H. T. T., & Do, H. T. T. (2026). Human resources and bank performance in the context of digital transformation. *Pacific Accounting Review*. https://doi.org/10.1108/PAR-01-2025-1298659

Rana, J., Daultani, Y., & Goswami, M. (2025). Exploring the impact of supply chain digital transformation on supply chain performance. *Business Strategy and the Environment*. https://doi.org/10.1002/bse.4157

Sarfraz, M., & Bhutta, M. K. (2026). Integrating Industry 5.0 and smart supply chains: A moderated serial mediation model. *Sustainable Development*. https://doi.org/10.1002/sd.70811

Sharma, P., & Dang, G. P. (2026). Unveiling the transformative role of artificial intelligence in improving business process performance. *Journal of Manufacturing Technology Management*. https://doi.org/10.1108/JMTM-04-2025-0308

Suparman, M., Suhardjo, I., & Crystina, C. (2026). Digital transformation and sustainability performance: An empirical study from Indonesia. *Asian Journal of Accounting Research*. https://doi.org/10.1108/AJAR-02-2025-0049

Thakur, A., Singla, K., & Mishra, K. A. (2026). Digital transformation and AI adoption: Scale development and validation. *International Journal of Educational Management*. https://doi.org/10.1108/IJEM-01-2025-1268102

Zhang, X., Hao, X., & Jia, X. (2026). Enhancing employees' readiness for digital transformation: SEM approach. *Journal of Enterprise Information Management*. https://doi.org/10.1108/JEIM-02-2025-1277228