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THE EFFECT OF ARTIFICIAL INTELLIGENCE IMPLEMENTATION ON DIGITAL GOVERNANCE PERFORMANCE MEDIATED BY DIGITAL INFRASTRUCTURE AND HUMAN RESOURCE COMPETENCE

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Abstract

This study aims to analyze the role of Artificial Intelligence (AI), human resource (HR) competence, and digital infrastructure in supporting the performance of Digital Governance in Indonesia. The results indicate that HR competence and digital infrastructure have a significant direct influence on Digital Governance performance, with HR competence being the most dominant factor. Meanwhile, AI implementation does not have a significant direct effect but exerts an indirect impact through the mediation of HR competence and digital infrastructure. These findings emphasize the importance of a systemic approach to improving Digital Governance performance by optimizing AI utilization supported by competent human resources and reliable infrastructure. This study contributes both theoretically and practically to supporting digital transformation in the public sector and provides a basis for evidence-based policy formulation toward more effective, efficient, and sustainable governance.

Keywords: Artificial Intelligence, HR Competence, Digital Infrastructure, Digital Governance, Digital Transformation, Governance

INTRODUCTION

The development of digital technology, particularly Artificial Intelligence (AI), has driven the transformation of governance in Indonesia toward becoming more efficient, transparent, and modern. The government has initiated several strategic programs, such as the National Artificial Intelligence Strategy (Stranas KA) 2020–2045 and the Electronic-Based Government System (SPBE), to build an inclusive and sustainable digital ecosystem (Pelealu, 2023). Stranas KA focuses on regulation, human resource capacity building, infrastructure development, and AI research enhancement to support Indonesia's 2045 vision. Meanwhile, SPBE aims to create an integrated digital government that improves bureaucratic efficiency and the quality of public services through the optimization of information technology. Both initiatives are complementary, with AI serving as a key catalyst to accelerate government digitalization, enhance data management, and promote adaptive and inclusive public service innovation to address future challenges (Putri Taopiq & Fuziyati, 2024).

The implementation of Artificial Intelligence (AI) within Indonesia's Electronic-Based Government System (SPBE) ecosystem is expected to accelerate bureaucratic reform, improve the quality of public services, and establish a modern governance framework. Practical examples include the use of big data for strategic decision-making, automation of administrative processes, and AI-powered public services such as chatbots and virtual assistants. Several important initiatives include the One Data Indonesia (SDI) Service Portal for data integration, the e-Procurement system for enhancing procurement transparency, and the PeduliLindungi application, which utilized AI during the COVID-19 pandemic. The digitalization of administrative services, such as Dukcapil Online and the online taxation system, also shows significant progress in improving service accessibility and accountability. However, challenges remain in AI adoption. According to the Government AI Readiness Index 2023, Indonesia ranks 42nd globally out of 193 countries and 4th in ASEAN, indicating both opportunities and areas for improvement in AI readiness to support more effective and responsive digital governance.

Indonesia's performance in the Government AI Readiness Index is measured through three main pillars: Government, Data and Infrastructure, and Technology. The Government pillar scored the highest at 73.85, reflecting strong policy support for AI development. The Data and Infrastructure pillar scored 67.32, indicating the availability of quality data and reliable digital infrastructure, although challenges remain in data integration, security, and technological access, especially in remote regions. The Technology pillar scored the lowest at 41.51, highlighting the need for strengthening AI technology capacity. These limitations in infrastructure and data affect AI implementation in the public sector, making infrastructure development and data management a national priority. In the UN E-Government Survey 2024, Indonesia achieved a score of 0.7991, placing it in the Very High E-Government Development Index (VHEGDI) category, with its ranking improving from 106 in 2008 to 64 in 2024, marking significant progress in digital government transformation.

Although Indonesia has entered the Very High E-Government Development Index (VHEGDI) category with a rank of 64 in the 2024 UN E-Government Survey, there are still many areas that require improvement to strengthen electronic-based governance. The increase in ranking from 77 in 2022 demonstrates progress, yet major challenges such as equitable access to digital infrastructure in remote areas and the integration and security of data management still demand serious attention. Additionally, developing human resources capable of utilizing information technology and AI remains a priority. This position highlights that Indonesia still lags behind leading ASEAN countries such as Singapore and Malaysia. Robust digital infrastructure—including fast internet connectivity and reliable data centers—is a crucial foundation for successful digital governance, and the lack thereof can lead to access and digital inequality.

Several previous studies have demonstrated the influence of Artificial Intelligence, digital infrastructure, and human resource competence on digital performance. However, other studies have also shown that digital infrastructure and human resources can mediate and strengthen the impact of artificial intelligence on digital governance performance (Toha et al, 2025). Therefore, this study examines all three factors to determine the most effective approach for improving digital governance performance in Indonesia.

This research aims to address this gap by exploring the influence of AI implementation, digital infrastructure, and human resource competence on the performance of digital governance in Indonesia. The study not only seeks to identify the most significant factors but also to provide practical recommendations for policymakers to strengthen key elements that support digital transformation in government. Thus, the findings are expected to make a significant contribution to the development of digital-based governance and serve as a valuable reference for future research discussing the effects of technology, infrastructure, and human resources on government performance.

REVIEW OF LITERATURE

Artificial Intelligence

According to Norvig and Russell (2020), Artificial Intelligence (AI) is the science and engineering of creating intelligent machines capable of thinking and acting rationally. This definition emphasizes AI's ability to understand its environment, make decisions, and take actions based on specific goals.

Technology Infrastructure

Technology infrastructure is a fundamental element that supports the implementation of information and communication technology (ICT) across various sectors, including digital governance. As stated by Gantz and Reinsel (2012), a reliable technological infrastructure enables organizations to process data efficiently, ensure stable connectivity, and improve operational efficiency across different processes.

Human Resource Competence

Human Resource (HR) competence plays a strategic role in supporting the successful implementation of new technologies, as explained in the Human Capital Theory proposed by Becker (1993). This theory positions human resources as the main asset that contributes significantly to productivity and innovation through the knowledge, skills, and abilities possessed by individuals.

Digital Governance Performance

Digital Governance Performance refers to the government's ability to utilize digital technologies to carry out governance functions efficiently, transparently, and accountably. According to Heeks (2006), Digital Governance is a framework that employs information and communication technology to enhance information management, accelerate administrative processes, and create cross-institutional connectivity within the government.

RESEARCH METHOD

Research Design

This study employs a mixed methods approach that combines quantitative and qualitative approaches. The quantitative approach is conducted using a survey method. The survey is carried out through questionnaires distributed to respondents—employees responsible for implementing Artificial Intelligence, managing digital infrastructure, and developing human resource competencies in support of Digital Governance. The survey aims to determine the effect of Artificial Intelligence implementation on Digital Governance performance, mediated by Digital Infrastructure and Human Resource Competence.

In addition, the qualitative approach is used to support the quantitative data findings. The in-depth interview questions are structured based on the conceptual framework developed earlier. The informants for the in-depth interviews are leaders from relevant ministries and government institutions.

Time and Location of Research

This research is conducted to understand how factors such as AI implementation, availability of digital infrastructure, and human resource competence influence Digital Governance performance. The results of this study are expected to provide strategic recommendations for the government to enhance the effectiveness of digital transformation in Indonesia.

The research period is planned to cover a specific timeframe that allows for the collection of primary data through surveys or interviews with relevant respondents, as well as the analysis of secondary data from official documents, policy reports, and previous studies related to Digital Governance in Indonesia. With this focus, the research is expected to make a meaningful contribution to supporting more effective and technology-based governance.

Population and Sampling

According to Sugiyono (2017), a population is a generalization area consisting of objects or subjects that have certain qualities and characteristics determined by the researcher to be studied and drawn as conclusions. Bungin (2009) also defines a research population as the entirety of research objects, which can include humans, animals, plants, phenomena, values, events, lifestyles, or other sources of research data.

In this study, the population consists of employees in government institutions in Indonesia who are involved in digital-based governance or the Electronic-Based Government System (SPBE). The population includes employees responsible for the implementation of Artificial Intelligence, management of digital infrastructure, and development of human resource competencies to support Digital Governance. This population includes employees from ministries, central government agencies, and local governments.

According to Sugiyono (2017), a sample is part of the population that possesses the same characteristics. The conclusions drawn from the sample are then applied to the population; therefore, the sample must accurately represent the population.

The sampling technique used in this study is non-probability sampling. Sugiyono (2017) explains that non-probability sampling is a sampling technique that does not give equal opportunity for every element or member of the population to be selected as a sample. The type of non-probability sampling used in this study is incidental sampling, which is a sampling technique based on chance—anyone who happens to meet the researcher can be used as a sample if they are deemed suitable and meet the criteria as a data source. The determination of the sample size in this study is based on the Slovin formula (Sugiyono, 2017).

$$n = \frac{N}{1 + Ne^2}$$

Description:
n: sample size
N: population size
e: allowance for inaccuracy or degree of tolerance

This population size is the population size (N) in the Slovin formula. The specified degree of tolerance of 0.1% is obtained by subtracting 100% from 90% accuracy. The following are the results of the sample calculation using the Slovin formula:

$$n = \frac{N}{1 + Ne^2} = \frac{324}{1 + 324.\,0{,}1^2} = 76{,}4 \sim 77$$

RESULT AND DISCUSSION

SEM-PLS analysis

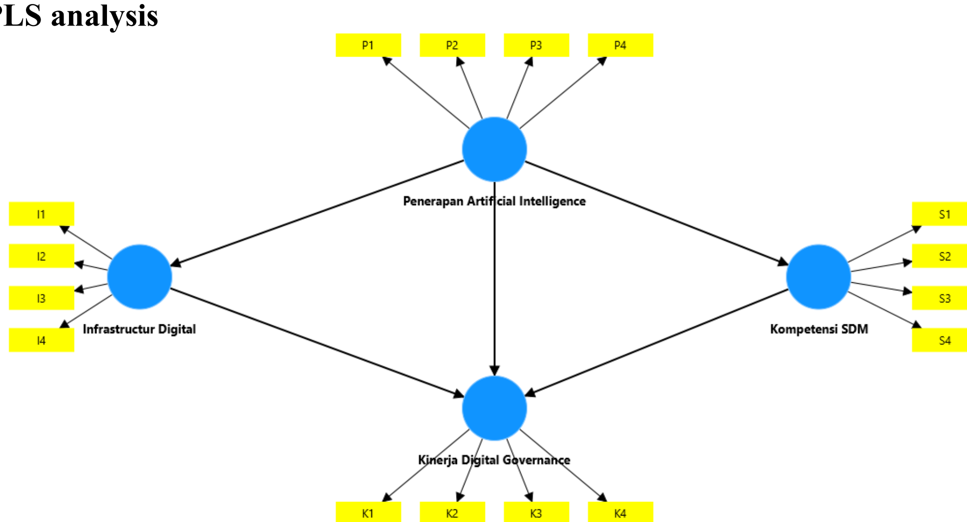

Figure 1.
2025 SEM-PLS Model Specifications

Outer Model Testing

The measurement model testing stage includes Convergent Validity, Discriminant Validity, and Composite Reliability testing. The results of the PLS analysis can be used to test research hypotheses if all indicators in the PLS model meet the requirements for convergent validity, discriminant validity, and composite reliability. To obtain the outer model test results, the PLS model must be estimated using algorithmic techniques. The following are the results of the SEM-PLS model estimation after being estimated using algorithmic techniques:

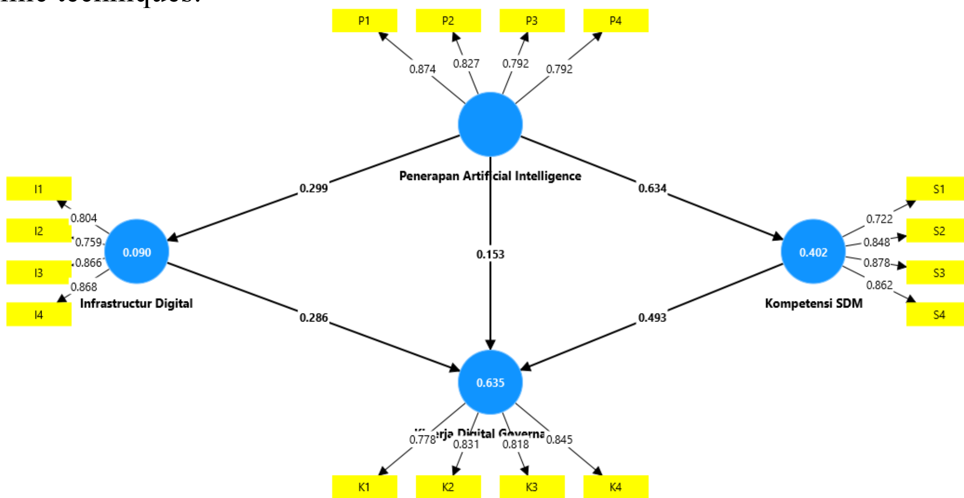

Figure 2.
SEM model estimation results using the 2025 PLS algorithm.

Convergent Validity Test

Convergent validity testing is conducted by examining the loading factor values of each indicator against its construct. For confirmatory research, the loading factor limit used is 0.7, while for exploratory research, the loading factor limit used is 0.6, and for developmental research, the loading factor limit used is 0.5. Because this research is confirmatory, the loading factor limit used is 0.7.

Based on the SEM model re-estimation results in Figure 7 above, all remaining variables in the model are valid. The test can proceed to the AVE test stage. The model's loading factor and AVE values are more clearly shown in Table 1:

Table 1.
Convergent Validity Test Results

Variable	Indicator	Loading Factor	Cut Value	AVE	Convergen Validity
Application of Artificial Intelligence	P1	0.874	0.7	0.676	valid
	P2	0.827	0.7		valid
	P3	0.792	0.7		valid
	P4	0.792	0.7		valid
Infrastructur Digital	I1	0.804	0.7	0.682	valid
	I2	0.759	0.7		valid
	I3	0.866	0.7		valid
	I4	0.868	0.7		valid
HR Competence	S1	0.722	0.7	0.689	valid

	S2	0.848	0.7		valid
	S3	0.878	0.7		valid
	S4	0.862	0.7		valid
Digital Governance Performance	K1	0.778	0.7	0.669	valid
	K2	0.831	0.7		valid
	K3	0.818	0.7		
	K4	0.845	0.7		valid

Source: Processed data (2025)

Discriminant Validity

Discriminant validity is conducted to ensure that each concept in each latent variable is distinct from the other variables. A model has good discriminant validity if the squared AVE value of each exogenous construct exceeds the correlation between that construct and the other constructs. The results of the discriminant validity test are as follows:

Table 3.
Discriminant validity according to the Fornell-Larcker test

	Infrastructur Digital	Digital Governance Performance	HR Competence	Application of Artificial Intelligence
Infrastructur Digital	0.826			
Digital Governance Performance	0.620	0.818		
HR Competence	0.584	0.757	0.830	
Application of Artificial Intelligence	0.299	0.552	0.634	0.822

Source: Processed data (2025)

Based on the results of the discriminant validity test in Table 2, the square root of the AVE for all constructs consistently exceeds the correlation coefficient of that construct with other constructs. It can be concluded that all constructs in this PLS model meet the required discriminant validity. In addition to using the Fornell-Larcker method, discriminant validity can also be assessed from the cross-loading values of each indicator against its construct. An indicator is deemed to meet the discriminant validity criteria if its cross-loading on its construct is higher than its cross-loading on other constructs.

Table 3.
Discriminant Validity by Cross-Loading Value

	Infrastructur Digital	Digital Governance Performance	HR Competence	Application of Artificial Intelligence
I1	0.804	0.617	0.537	0.240

I2	0.759	0.349	0.442	0.246
I3	0.866	0.538	0.516	0.303
I4	0.868	0.484	0.410	0.194
K1	0.485	0.778	0.700	0.507
K2	0.568	0.831	0.633	0.459
K3	0.495	0.818	0.600	0.459
K4	0.467	0.845	0.515	0.357
P1	0.232	0.497	0.550	0.874
P2	0.288	0.483	0.562	0.827
P3	0.223	0.394	0.384	0.792
P4	0.237	0.427	0.562	0.792
S1	0.429	0.506	0.722	0.419
S2	0.441	0.612	0.848	0.603
S3	0.469	0.645	0.878	0.544
S4	0.590	0.730	0.862	0.526

Source: Processed data (2025)

Based on the results of the discriminant validity test in Table 3, it shows that all indicators have the highest value for their construct, not for other constructs. This indicates that all indicators meet the requirements for discriminant validity. In addition to the Fornell-Larcker test and cross-loading, discriminant validity can also be determined by examining the Heterotrait-Monotrait Ratio (HTMT) values between constructs. HTMT is a recommended alternative method for assessing discriminant validity. This method uses a multitrait-multimethod matrix as the measurement basis. The HTMT value must be <0.9 to ensure discriminant validity between two reflective constructs (Henseler et al. 2015). In this test, a construct in a PLS model is considered to have met discriminant validity if the HTMT value between that construct and other constructs does not exceed 0.9.

Table 4.
Discriminant Validity Based on HTMT Values

	Infrastructur Digital	**Digital Governance Performance**	**HR Competence**	**Application of Artificial Intelligence**
Infrastructur Digital				
Digital Governance Performance	0.711			
HR Competence	0.679	0.883		

Application of Artificial Intelligence	0.351	0.645	0.738

Source: Processed data (2025)

Based on the results of the discriminant validity test in Table 4, the HTMT value between constructs did not exceed 0.9, indicating that all constructs in the PLS model met the required discriminant validity criteria. The results of the three discriminant validity testing methods indicate that the outer PLS model met the required discriminant validity criteria. The testing continued with the composite reliability test.

Composite Reliability

Construct reliability can be assessed from the Cronbach's alpha and composite reliability values for each construct. The recommended composite reliability and Cronbach's alpha values are greater than 0.7. However, in development research, due to the low factor loading limit (0.5), low composite reliability, and Cronbach's alpha values are acceptable as long as the convergent and discriminant validity requirements are met.

Table 5.
Composite Reliability

	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
Infrastructur Digital	0.846	0.862	0.895	0.682
Digital Governance Performance	0.835	0.837	0.890	0.669
HR Competence	0.848	0.861	0.898	0.689
Application of Artificial Intelligence	0.840	0.848	0.893	0.676

Based on the analysis results in Table 5, the composite reliability and Cronbach's alpha values for all constructs also exceeded 0.7, indicating that all constructs met the required reliability.

Model Goodness of Fit Assessment

Model goodness-of-fit testing is conducted to ensure that the constructed PLS model fits the analyzed data and represents the actual population. The goodness of fit of the PLS model can be assessed through the R-square value. According to Chin (1998), an R-square value > 0.67 indicates a strong predictive ability for the endogenous construct. A value between 0.33 and 0.67 indicates moderate predictive ability, and a value between 0.19 and 0.33 indicates a weak model in predicting endogenous variables.

Based on the analysis results in the R-square Table, it is known that:

a. The Digital Governance Performance variable has an R-square value of 0.635, which is considered moderate. This indicates that the combination of the variables of Artificial Intelligence implementation, digital infrastructure, and HR competency can explain 63.5% of the variation in digital governance performance.
b. The HR Competency variable has an R-square value of 0.402, which is also in the moderate category, indicating that HR competency is quite well explained by the application of Artificial Intelligence in this model.

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c. Meanwhile, the Digital Infrastructure variable has an R-square value of 0.090, which is in the weak category, indicating that the application of Artificial Intelligence can only explain a small portion (9%) of the variation in digital infrastructure.

Thus, the SEM-PLS model used in this study has moderately strong predictive power for the Digital Governance Performance and HR Competency variables, but is still weak in explaining the Digital Infrastructure variable. This indicates that the model is generally reliable, but needs strengthening or the addition of other variables to better explain digital infrastructure development in the context of AI-based government transformation.

Table 6.
R Square

	R-square	R-square adjusted
Infrastructur Digital	0.090	0.080
Digital Governance Performance	0.635	0.623
HR Competence	0.402	0.396

Source: Processed data (2025)

Testing the Influence Between Variables

In PLS analysis, once the model has been proven to fit, testing the influence between variables can be performed. These influence tests include direct and indirect influence tests. The following are the results of the SEM PLS model estimation using the bootstrapping method:

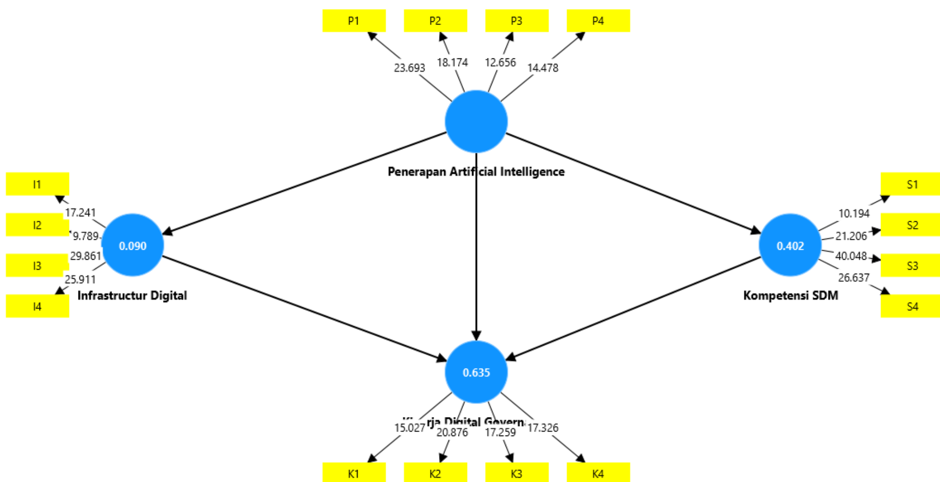

Figure 3.
2025 Bootstrapping Model Estimation Results

Based on the PLS model estimation results using the bootstrapping technique for 94 samples, the following results were obtained for testing the direct and indirect effects between variables:

Direct Effect

The direct effect is the direct influence of an exogenous variable on an endogenous variable. In SEM-PLS analysis, the significance and direction of the direct effect are determined by the p-value, t-statistic, and the path coefficients connecting the endogenous and exogenous variables. If the p-value is <0.05 and the t-statistic is >1.96 (two-tailed t-value, α 5%), then it is concluded that the exogenous variable has a significant effect on the endogenous variable, with the direction of the effect corresponding to the sign of the path coefficient. Furthermore, if the p-value is >0.05 and the t-statistic is <1.96 (two-tailed t-value, α 5%), then it is concluded that the exogenous variable does not have a significant effect on the endogenous variable (Hair et al. 2018).

Table 7.
Results of the Direct Effect Test

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Infrastructur Digital -> Digital Governance Performance	0.286	0.289	0.079	3.608	**0.000**
HR Competence -> Digital Governance Performance	0.493	0.496	0.105	4.712	**0.000**
Application of Artificial Intelligence -> Infrastructure Digital	0.299	0.310	0.093	3.235	**0.001**
Application of Artificial Intelligence -> Digital Governance Performance	0.153	0.145	0.107	1.432	**0.152**
Application of Artificial Intelligence -> HR Competence	0.634	0.639	0.058	10.989	**0.000**

Source: Processed data (2025)

Based on the results of the direct influence test, the following results were obtained:

1. **Digital Infrastructure → Digital Governance Performance**
   Digital infrastructure has a significant positive effect on digital governance performance, as indicated by sig. = 0.000 < 0.05, T statistic 3.608 > 1.96, and a positive path coefficient of 0.286. This means that the better the digital infrastructure of a government agency, the higher its digital governance performance. Conversely, the worse the digital infrastructure, the lower its digital governance performance.
2. **Human Resource Competence → Digital Governance Performance**
   Human resource (HR) competence has a significant positive effect on digital governance performance, as indicated by sig. = 0.000 < 0.05, T statistic 4.712 > 1.96, and a positive path coefficient of 0.493. This means that the higher the human resource competency, the higher the digital governance performance. Conversely, the lower the human resource competency, the lower the digital governance performance.
3. **Artificial Intelligence Implementation → Digital Infrastructure**
   The implementation of artificial intelligence (AI) has a significant positive effect on digital infrastructure, as indicated by a sig. = 0.001 < 0.05, a T-statistic of 3.235 > 1.96, and a positive path coefficient of 0.299. This means that the more optimal the implementation of AI, the better the strengthening of digital infrastructure. Conversely, if the implementation of AI is low, the digital infrastructure tends to be weak.

4. **Artificial Intelligence Implementation → Digital Governance Performance**
   The implementation of artificial intelligence (AI) does not have a significant positive effect on digital governance performance, as indicated by a sig. = 0.152 > 0.05, a T-statistic of 1.432 < 1.96, and a positive path coefficient of 0.153. This means that the level of AI implementation does not directly influence the level of digital governance performance.
5. **Artificial Intelligence Implementation → Human Resource Competence**
   The implementation of artificial intelligence (AI) has a significant positive effect on human resource (HR) competency, as indicated by a sig. = 0.000 < 0.05, a T-statistic of 10.989 > 1.96, and a positive path coefficient of 0.634. This means that the higher the level of AI implementation, the higher the HR competency in supporting digital governance. Conversely, if AI implementation is low, HR competency tends to be weak.

The following table presents the results of the indirect influence test for this study:

Table 8.
Results of the Indirect Effect Test

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T statistics (|O/STDEV|)	P values
Application of Artificial Intelligence -> Performance Digital Governance	0.153	0.145	0.107	1.432	**0.152**
Application of Artificial Intelligence -> HR Competence	0.634	0.639	0.058	10.989	**0.000**

Source: Processed data (2025)

Based on the results of the indirect effect test, the following results were obtained:

1. **Artificial Intelligence Implementation → Human Resource Competence → Digital Governance Performance**
   The implementation of artificial intelligence (AI) has a significant positive indirect effect on digital governance performance through the mediation of human resource (HR) competency, as indicated by sig. = 0.000 < 0.05, T statistic 4.057 > 1.96, and an indirect path coefficient of 0.313. This indicates that AI can significantly improve digital governance performance when accompanied by increased HR competency. In other words, HR competency significantly mediates the relationship between AI implementation and digital governance performance.
2. **Artificial Intelligence Implementation → Digital Infrastructure → Digital Governance Performance**
   The implementation of artificial intelligence (AI) has a significant positive indirect effect on digital governance performance through the mediation of digital infrastructure, as indicated by sig. = 0.011 < 0.05, T statistic 2.534 > 1.96, and an indirect path coefficient of 0.086. This indicates that digital infrastructure significantly mediates the relationship between AI implementation and digital governance performance. This means that AI implementation followed by strengthening digital infrastructure will drive more effective digital government performance.

Coefficient of Determination

The coefficient of determination indicates the magnitude of the contribution of all exogenous variables to the endogenous variables. The coefficient of determination can be seen from the Adjusted R Square value. This value ranges from 0 to 1 or can also be interpreted as a percentage (0 to 100%). A larger coefficient of determination indicates a greater amount of endogenous variance explained by the exogenous variables, while a smaller coefficient of determination indicates a low influence of the exogenous variables on the endogenous variables. This is because there are still quite a number of factors outside the exogenous variables that can influence the endogenous variables.

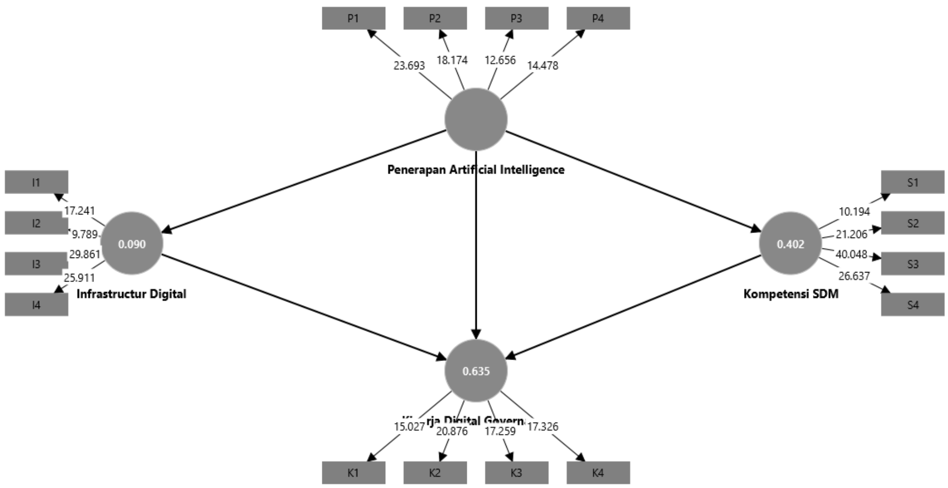

Figure 4.
Coefficient of Determination 2025

Based on the data processing results, the R-square value for Digital Infrastructure was 0.090, indicating that 9% of the variability in the Digital Infrastructure variable is influenced by the Implementation of Artificial Intelligence, while the remaining 91% is influenced by factors outside the model.

Furthermore, the R-square value for Human Resource Competence was 0.402, indicating that 40.2% of the variability in Human Resource Competence is influenced by the Implementation of Artificial Intelligence, and the remaining 59.8% is influenced by factors outside the model.

The R-square value for Digital Governance Performance was 0.635, indicating that 63.5% of the variability in Digital Governance Performance is influenced by the Implementation of Artificial Intelligence, Digital Infrastructure, and Human Resource Competence, while the remaining 36.5% is influenced by factors outside these three variables.

Thus, this model has strong explanatory power for Digital Governance Performance, moderate power for Human Resource Competence, and low power for Digital Infrastructure.

Hypothesis Testing

The hypothesis testing in this study was conducted based on the results of the SEM-PLS analysis in Table 9. The following is a summary of the results of the hypothesis testing in this study:

Table 9.
Summary of Hypothesis Testing Results

Hypothesis	Variable Measurement	Original sample (O)	T statistics (|O/STDEV|)	P values	Description
H1	The application of Artificial Intelligence has a significant impact on the performance of Digital Governance	0.153	1.432	**0.152**	**Decline**
H2	The application of Artificial Intelligence has a significant impact on human resource competency.	0.634	10.989	**0.000**	**Accepted**
H3	The application of Artificial Intelligence has a significant impact on digital infrastructure	0.299	3.235	**0.001**	**Accepted**
H4	Human resource competency has a significant influence on Digital Governance performance	0.493	4.712	**0.000**	**Accepted**
H5	Digital infrastructure has a significant impact on Digital Governance performance	0.286	3.608	**0.000**	**Accepted**
H6	Human resource competency mediates the influence of Artificial Intelligence implementation on Digital Governance performance	0.313	4.057	**0.000**	**Accepted**
H7	Digital infrastructure mediates the influence of Artificial Intelligence implementation on Digital Governance performance	0.086	2.534	**0.011**	**Accepted**

Source: Processed data (2025)

CONCLUSION

Based on the results of the analysis and discussion, it can be concluded that the implementation of Artificial Intelligence (AI), human resource (HR) competence, and digital infrastructure play a strategic role in supporting the performance of Digital Governance in Indonesia. This study demonstrates that adequate HR competence and digital infrastructure readiness are crucial elements in ensuring the success of digital-based government governance. In other words, the performance of Digital Governance does not solely depend on the adoption of advanced technologies but also on the preparedness of human resources and supporting systems.

The results show that the implementation of AI does not have a direct and significant effect on Digital Governance performance. However, AI significantly influences HR competence and digital infrastructure, which in turn positively impact Digital Governance performance through mediation paths. These findings support the second, fifth, and sixth research objectives, emphasizing the importance of mediation in bridging the effect of AI on digital government performance. Meanwhile, HR competence is the most dominant factor directly affecting Digital Governance performance, followed by digital infrastructure. This supports the third and fourth research objectives, which highlight the importance of organizational readiness in terms of human and technological aspects.

Therefore, this study concludes that efforts to improve Digital Governance performance in Indonesia must be carried out through a systemic approach — by optimizing the utilization of AI supported by enhanced HR competence and the development of inclusive and reliable digital infrastructure. This research provides both theoretical and practical contributions to supporting digital transformation in the public sector and serves as a foundation for formulating more adaptive and evidence-based policies toward effective, efficient, and sustainable government governance.

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