



Digital Competence and Employee Performance: Mediating AI Support, Moderating Organizational Support in Gorontalo City

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ARTICLE INFO

Keywords: AI Support, Digital Competence, Employee Performance, Organizational Support, Social Exchange Theory

Received : 3 August 2026

Revised : 18 September 2026

Accepted : 19 October 2026

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ABSTRACT

This study aims to examine the effect of digital competence on employee performance in public service institutions in Gorontalo City, by testing the mediating role of AI support and the moderating role of organizational support. A quantitative approach was employed through a survey of 200 civil servants across four institutions, namely the Health Office, the Population and Civil Registration Office, the Investment and One-Stop Integrated Licensing Service Office, and the Manpower, Cooperatives, and MSME Office of Gorontalo City, with data analyzed using Partial Least Squares Structural Equation Modeling through SmartPLS 4.0. The results show that digital competence significantly affects both employee performance and AI support, AI support significantly affects employee performance while partially mediating that relationship, and organizational support significantly strengthens the relationship between digital competence and employee performance, although its direct effect moves in the opposite direction. These findings conclude that individual competence and organizational technological support are complementary resources, while the effectiveness of organizational support is contextual and depends on employees' digital readiness, thereby contributing theoretically to the development of Social Exchange Theory within the context of public sector digital transformation.

INTRODUCTION

Digital transformation is essential for modernizing local government services, but its implementation often depends on civil servants' digital competence and organizational support. In Gorontalo City, only 34% of civil servants across four public service agencies are considered digitally competent, while the implementation of e-government under Mayoral Regulation No. 5 of 2025 had achieved 42% of its 70% target by March 2026. An internal BKPSDM survey (2026) found that 67% of employees struggled to operate digital government applications, while 58% identified inadequate AI-related support as a major performance barrier. These findings indicate that public-sector digital transformation involves both workforce capability and organizational support challenges.

Previous studies have established a relationship between digital competence and employee performance but identified different mechanisms, including employee agility (Nadzim & Halim, 2022), work motivation (Sulaiman et al., 2025), and AI self-efficacy (Li & Geng, 2026). Other research highlights the importance of organizational and leadership support in strengthening technology-related performance outcomes (Chatterjee et al., 2023; Wang et al., 2025). However, limited research has simultaneously examined AI support as a mediator and organizational support as a moderator within the same model, particularly among civil servants in Eastern Indonesia.

This study addresses the gap by testing an integrated model in which AI support acts as a parallel mediator, while organizational support independently moderates the direct relationship between digital competence and employee performance. This approach distinguishes mediation and moderation as two complementary, non-sequential mechanisms. It also contributes empirical evidence from four public service agencies in Gorontalo City, a mid-sized Eastern Indonesian city undergoing policy-driven digital transformation.

The findings reveal that organizational support significantly strengthens the relationship between digital competence and employee performance, although its direct effect on performance is significantly negative. This unexpected result suggests that organizational support may primarily enhance the effectiveness of employees' existing digital capabilities rather than independently improve performance. Overall, the study provides practical guidance for Gorontalo City's digital transformation and advances understanding of how digital competence, AI support, and organizational support jointly influence public-sector employee performance.

LITERATURE REVIEW

Social Exchange Theory

This study is grounded in Social Exchange Theory (SET), developed by Blau (1964) and further elaborated by Cropanzano and Mitchell (2005). SET explains that relationships between individuals and organizations are based on reciprocity: when employees receive valuable resources, support, or fair treatment, they tend to reciprocate through greater effort, commitment, and improved work performance. In organizations, technological resources such as

AI support and organizational support can encourage employees to contribute more effectively.

Within this study, SET provides the theoretical foundation connecting all research variables. Digital competence represents employees' personal resources, while AI support and organizational support serve as organizational inducements that encourage reciprocal contributions. Employee performance represents the tangible outcome of this exchange relationship. This framework explains the direct relationships (H1, H2, and H3), the mediating relationship (H4), and the moderating relationship (H5), suggesting that organizational resources and support help employees translate their digital competence into improved performance.

Digital Competence as a Personal Resource in the Exchange Relationship

Digital competence encompasses the knowledge, skills, and attitudes required to use digital technologies effectively, including technical abilities, information management, communication, collaboration, creativity, critical thinking, and problem-solving (Oberländer et al., 2020; van Laar et al., 2019). From the perspective of Social Exchange Theory, digital competence represents a personal resource that enables employees to fulfill their responsibilities and improve performance. Previous studies have confirmed its positive relationship with employee performance through mechanisms such as employee agility and improved public service quality (Nadzim & Halim, 2022; Ingsih et al., 2024; Sulaiman et al., 2025; Maulana et al., 2026). Accordingly, H1 proposes that digital competence significantly affects employee performance.

Digital competence also influences employees' ability to recognize and utilize organizational resources, particularly AI support. Employees with stronger digital skills tend to be more confident in exploring AI-based systems and integrating them into their work. This relationship is supported by Li and Geng (2026), who emphasize AI self-efficacy, and Zhang and Yu (2025), who identify a link between digital literacy and AI support utilization in government organizations. These findings provide a theoretical basis for examining the effect of digital competence on AI support.

H2: Digital Competence has a significant effect on AI Support.

AI Support as an Organizational Inducement

AI support is grounded in the facilitating conditions framework of UTAUT (Venkatesh et al., 2003) and perceived organizational support theory (Eisenberger et al., 2020). From the perspective of Social Exchange Theory, AI support represents an organizational resource provided through infrastructure, training, and technical assistance. Employees who perceive such support may reciprocate by increasing their work contributions. Previous studies have demonstrated that AI support improves work adaptability among public-sector employees (Zhang & Yu, 2025) and contributes to employee performance (Maulana et al., 2026). Therefore, H3 proposes that AI support significantly affects employee performance.

However, Li and Geng (2026) found that AI usage improves performance significantly only through AI self-efficacy and digital human resource

management practices. This suggests that digital competence may influence employee performance both directly and indirectly through AI support. Digitally competent employees are better able to utilize organizational AI resources, which can enhance their performance through reciprocal contributions. This mediation relationship is examined using the bias-corrected bootstrap approach (Preacher & Hayes, 2008) and the Variance Accounted For (VAF) criterion (Hair et al., 2017), providing the basis for H4.

H4: AI Support mediates the effect of Digital Competence on Employee Performance.

Organizational Support as a Reinforcer of the Reciprocity Norm

Organizational Support is grounded in the Perceived Organizational Support (POS) theory of Eisenberger et al. (2020), which describes employees' beliefs that their organization values their contributions and cares about their well-being. Based on Social Exchange Theory, greater perceived support strengthens employees' sense of reciprocity, encouraging them to translate their digital competence into improved performance. Thus, organizational support functions primarily as a factor that strengthens the relationship between digital competence and employee performance.

Previous studies support this moderating role. Wang et al. (2025) found that perceived organizational support strengthens the relationship between digital technology demands and innovative behavior through enhanced career resilience. Similarly, Chatterjee et al. (2023) demonstrated that digital leadership capability moderates the relationship between the digital workplace and organizational performance. These findings provide the basis for the fifth hypothesis (H5), which proposes that Organizational Support significantly moderates the relationship between Digital Competence and Employee Performance.

H5: Organizational Support moderates the direct effect of Digital Competence on Employee Performance.

Employee Performance as the Employee's Reciprocal Contribution

Employee performance in this study is examined based on the normative framework of Regulation of the Minister of Administrative and Bureaucratic Reform No. 6 of 2022 on Performance Management of Civil Apparatus, which affirms that ASN performance management focuses on employees' work results and work behavior on an ongoing basis, comprising four stages: performance planning (setting performance expectations), performance implementation and monitoring, periodic and annual performance evaluation, and follow-up on evaluation results. Work behavior under this regulation comprises five aspects, namely service orientation, commitment, work initiative, teamwork, and leadership (KEMENPAN RB, 2022).

This normative framework is consistent with the individual work performance framework of Koopmans et al., (2014): the achievement of performance expectations/work results represents task performance, while the five aspects of work behavior represent the dimensions of contextual performance and counterproductive work behavior. From a Social Exchange

Theory perspective, employee performance, whether measured through work results or work behavior, represents the tangible return side of the exchange relationship, that is, the contribution employees provide in response to the personal resources they possess and the support they receive from the organization.

Theoretical Synthesis and Conceptual Framework

Most studies in this field use quantitative cross-sectional surveys and PLS-SEM, which support predictive modeling and simultaneous mediation and moderation analysis (Hair et al., 2019). Based on Social Exchange Theory, this study conceptualizes digital competence as personal capital, AI support as a mediating inducement, and organizational support as a moderator that strengthens reciprocal contributions to employee performance. Although these variables have been widely studied, previous research has generally examined them separately or through single mediation pathways. This study addresses the gap by integrating AI support as a mediator and organizational support as a moderator within a unified framework explaining the relationship between digital competence and employee performance. The conceptual framework summarizes these relationships through five hypotheses.

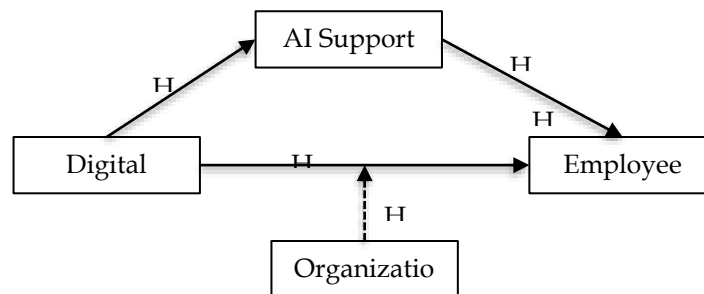


Figure 1. Conceptual Framework

Figure 1 shows that AI Support functions as a parallel mediator on the path from Digital Competence to Employee Performance (H2 and H4), while Organizational Support functions as a moderator that strengthens the direct path between Digital Competence and Employee Performance (H5). These two mechanisms operate side by side rather than sequentially, such that this study's model tests all five hypotheses (H1-H5) together within a single Social Exchange Theory framework.

METHODOLOGY

Research Design

This study employs a quantitative approach with an explanatory cross-sectional survey design, aiming to test the direct, mediating, and moderating relationships among variables formulated on the basis of Social Exchange Theory within the study's conceptual framework.

Population, Sample, and Sampling Technique

The population of this study comprises all civil servants (ASN) working at four public service agencies within the Gorontalo City Government. The sample

was set at 200 respondents, selected using a stratified random sampling technique based on rank and work unit, in accordance with the sample-adequacy guidelines for Structural Equation Modeling (SEM) analysis proposed by (Hair et al., 2022).

Operational Definitions and Measurement of Variables

Each variable is measured using a five-point Likert-scale self-report instrument, constructed from indicators derived directly from the theoretical review in the preceding section.

Tabel 1. Operational Definitions and Measurement of Variables

Variable	Operational Definition	Indicators	Scale
Digital Competence (X)	A combination of knowledge, skills, and attitudes enabling employees to effectively utilize digital technology (Oberländer et al., 2020; van Laar et al., 2019).	Technical skills; digital information management; digital communication; digital collaboration; critical thinking/ digital problem-solving; adaptation to new technology	5-point Likert
AI Support (Z)	Employees' perception of the availability of resources, infrastructure, training, and organizational assistance supporting effective AI use (Eisenberger et al., 2020; Venkatesh et al., 2003).	Availability of AI systems; AI use training; system compatibility; technical assistance; leadership support; clarity of AI policy	5-point Likert
Organizational Support (M)	Employees' general belief that the organization values their contribution and cares about their well-being (Eisenberger et al., 2020)	Procedural justice; recognition of contribution; concern for well-being; clarity of organizational policy; general leadership support	5-point Likert
Employee Performance (Y)	The work results and work behavior of civil servants (ASN), managed through a cycle of performance planning, implementation, evaluation, and follow-up, as regulated under Regulation of the Minister of Administrative and Bureaucratic Reform No. 6 of 2022 on Performance Management of Civil Apparatus (KEMENPAN RB, 2022).	Achievement of performance expectations/targets (work results); service orientation; commitment; work initiative; teamwork; leadership	5-point Likert

Data Collection Technique

Data were collected through a survey using a closed-ended questionnaire on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). The instrument was validated through expert judgment prior to field use. Data collection was conducted face-to-face using printed questionnaires with direct

assistance from research team members, to ensure completeness and clarity of respondents' answers.

Data Analysis Technique

Data were analyzed using the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach with SmartPLS 4.0, as this approach suits predictive models with moderate sample sizes and can test mediation and moderation simultaneously (Hair et al., 2019). The analysis began with an evaluation of the measurement model (outer model) through convergent validity (outer loadings and Average Variance Extracted), reliability (Cronbach's alpha and Composite Reliability), and discriminant validity (the Fornell-Larcker criterion and the Heterotrait-Monotrait Ratio).

Once the measurement model met the required criteria, the analysis proceeded to the structural model (inner model), covering collinearity (VIF), the coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2) through the blindfolding procedure. The direct-effect hypotheses (H1, H2, H3) were tested through bootstrapping with 5,000 resamples, using a t-statistic above 1.96 and a p-value below 0.05 as the significance criteria. The mediation hypothesis (H4) was tested through a bootstrapping bias-corrected confidence interval approach Preacher & Hayes (2008) together with the Variance Accounted For (VAF) (Hair et al., 2017), while the moderation hypothesis (H5) was tested through the product indicator approach, with the interaction coefficient's significance assessed through the same bootstrapping procedure.

RESULT

Respondent Demographics

The characteristics of the respondents are presented in Table 1 to provide a general overview of the composition of civil servants who served as the unit of analysis in this study.

Table 2. Respondent Characteristics (n = 200)

Characteristic	Category	Frequency	Percentage
Gender	Male	84	42.0%
	Female	116	58.0%
Age	< 30 years	36	18.0%
	30-39 years	68	34.0%
	40-49 years	62	31.0%
	≥ 50 years	34	17.0%
Educational Attainment	Senior High School/Diploma	24	12.0%
	Bachelor's Degree	122	61.0%
	Master's Degree	50	25.0%
Tenure	Doctoral Degree	4	2.0%
	< 5 years	42	21.0%
	5-10 years	66	33.0%
	11-20 years	58	29.0%
	> 20 years	34	17.0%
Institutional Unit	Health Office	62	31.0%
	Population and Civil Registration Office	54	27.0%
	Investment and One-Stop Integrated	46	23.0%
	Licensing Service Office		

Manpower, Cooperatives, and MSME Office	38	19.0%
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Source: Researcher's Processed Data, 2026

Based on Table 2, the majority of respondents hold a bachelor's degree with varying lengths of tenure, reflecting a composition of public service civil servants who are reasonably experienced yet still dominated by the productive age group of 30 to 49 years. The four institutions serving as research sites, namely the Health Office, the Population and Civil Registration Office, the Investment and One-Stop Integrated Licensing Service Office, and the Manpower, Cooperatives, and MSME Office of Gorontalo City, are institutions characterized by a high intensity of public service delivery and digitally based administrative transactions, making them relevant settings for measuring digital competence as a work capacity actively used on a daily basis.

Descriptive Statistics of Research Variables

Descriptive statistics for each variable were calculated based on respondents' mean scores on a 1 to 5 scale, with class interval categorization following Sugiyono (2017): 1.00-1.80 very low, 1.81-2.60 low, 2.61-3.40 moderate, 3.41-4.20 high, and 4.21-5.00 very high.

Table 3. Descriptive Statistics of Research Variables

Variable	Mean	Std. Deviation	Category
Digital Competence	3.92	0.58	High
AI Support	3.75	0.62	High
Organizational Support	3.68	0.71	High
Employee Performance	4.05	0.55	High

Source: Researcher's Processed Data, 2026

Based on Table 3, all four variables fall into the high category, indicating that respondents in this study generally perceive digital competence, AI support, and organizational support in their workplace as reasonably favorable, consistent with the likewise high perceived level of employee performance. Nevertheless, the relatively larger standard deviation observed for Organizational Support (0.71) indicates greater variation in perception among respondents compared to the other variables, which leaves room for direct-effect test results that do not always align neatly with its descriptive mean pattern.

Common Method Bias Test

Because all data in this study were collected from a single source (self-report) through one instrument at a single point in time, the possibility of common method bias needs to be examined beforehand to ensure that the relationships observed among variables genuinely reflect substantive relationships rather than a mere artifact of the data collection method (Podsakoff et al., 2003). The examination was carried out through Harman's single-factor test, in which all 40 indicator items were entered into an unrotated exploratory factor analysis; if the resulting single factor accounts for less than 50% of the total variance, the data can be considered free from serious method bias.

Table 4. Common Method Bias Test Results

Test	Value	Threshold	Remark
Harman's Single-Factor Test	36.8% of variance explained by a single factor	< 50%	No serious CMB indication

Source: Researcher's Processed Data, 2026

Based on Table 4, the single factor that emerged accounted for only 36.8% of the total variance, well below the 50% threshold. This result indicates that common method bias does not pose a meaningful threat to the validity of this study's findings.

Convergent Validity Test

Convergent validity was examined to ensure that the indicators of each construct consistently measure the same underlying concept, based on two parameters, namely outer loading and Average Variance Extracted (AVE). Fornell & Larcker (1981), later reaffirmed by Hair et al., (2019), established that an outer loading above 0.7 and an AVE above 0.5 are sufficient to declare a construct convergently valid.

Table 5. Convergent Validity Test Results

Construct	Outer Loading Range	AVE	Remark
Digital Competence	0.861-0.910	0.792	Criteria met
AI Support	0.858-0.908	0.789	Criteria met
Organizational Support	0.856-0.905	0.778	Criteria met
Employee Performance	0.862-0.913	0.802	Criteria met

Source: Researcher's Processed Data, 2026

Based on Table 5, all 40 items in this study have outer loadings above 0.7, and none of the four constructs has an AVE below 0.5, so no item needed to be eliminated from the measurement model. In other words, convergent validity is confirmed for all four constructs.

Reliability Test

The internal consistency of the indicators in measuring their respective constructs was tested through two complementary parameters, namely Cronbach's alpha and Composite Reliability (CR), with a threshold of > 0.7 as recommended by Nunnally (1978) and Hair et al., (2019).

Table 6. Reliability Test Results

Construct	Cronbach's α	CR (ρ_c)	Remark
Digital Competence	0.971	0.974	Reliable
AI Support	0.970	0.974	Reliable
Organizational Support	0.969	0.972	Reliable
Employee Performance	0.972	0.976	Reliable

Source: Researcher's Processed Data, 2026

Based on Table 6, both parameters consistently fall within the range of 0.97 to 0.98 across all constructs, well above the minimum threshold required. The reliability of the research instrument can therefore be considered excellent.

Discriminant Validity Test, Fornell-Larcker Criterion

Discriminant validity was examined to demonstrate that the four constructs are genuinely distinct from one another at the empirical level. The first criterion applied was the Fornell-Larcker criterion by Fornell & Larcker (1981), under which the square root of a construct's AVE must exceed its correlation with any other construct in the model.

Table 7. Discriminant Validity Test Results, Fornell-Larcker Criterion

	Digital Competence	AI Support	Organizational Support	Employee Performance
Digital Competence	0.890			
AI Support	0.524	0.888		
Organizational Support	0.071	0.008	0.882	
Employee Performance	0.557	0.737	-0.095	0.895

Source: Researcher's Processed Data, 2026

Based on Table 7, the diagonal value in every row and column consistently exceeds the surrounding correlation values, so the Fornell-Larcker requirement is satisfied for all four constructs under study.

Discriminant Validity Test, Heterotrait-Monotrait Ratio (HTMT)

Given that the Fornell-Larcker criterion is considered less sensitive in detecting discriminant validity issues in models with reflective constructs, Henseler et al., (2015) proposed the Heterotrait-Monotrait ratio (HTMT) as a complementary test, with a strict threshold below 0.85 for conceptually distinct construct pairs.

Table 8. Discriminant Validity Test Results, HTMT

Construct Pair	HTMT	Remark
Digital Competence ↔ AI Support	0.538	Met
Employee Performance ↔ AI Support	0.758	Met
Employee Performance ↔ Digital Competence	0.572	Met
Organizational Support ↔ AI Support	0.049	Met
Organizational Support ↔ Digital Competence	0.087	Met
Organizational Support ↔ Employee Performance	0.088	Met

Source: Researcher's Processed Data, 2026

Based on Table 8, every construct pair falls well below the 0.85 threshold, including the highest value observed, between Employee Performance and AI Support, at 0.758. This result reinforces the conclusion drawn from the Fornell-Larcker criterion that the four constructs are clearly distinguishable from one another.

Collinearity Test

Prior to a full evaluation of the structural model, the level of collinearity among predictors was examined through the Variance Inflation Factor (VIF), to ensure no excessive correlation among predictors that could distort the estimation of path coefficients. Hair et al., (2019) set a general threshold of 5, while Kock (2015) recommends a more conservative threshold of 3.3, which also serves as an additional indicator of the absence of common method bias.

Table 9. Collinearity Test Results

Predictor Path	VIF	Remark
Digital Competence → AI Support	1.00	Free of collinearity
Digital Competence → Employee Performance	1.39	Free of collinearity
AI Support → Employee Performance	1.44	Free of collinearity
Organizational Support → Employee Performance	1.02	Free of collinearity
Interaction (OS × DC) → Employee Performance	1.03	Free of collinearity

Source: Researcher's Processed Data, 2026

Based on Table 9, VIF values across all paths range from 1.00 to 1.44, well below even the stricter 3.3 threshold. Multicollinearity can therefore be ruled out as a concern in this study's structural model.

Coefficient of Determination (R^2)

The model's capacity to explain variation in the endogenous constructs was assessed through the coefficient of determination (R^2), following the categorization proposed by Hair et al., (2013): values above 0.75 are considered substantial, 0.50 to 0.75 moderate, and 0.25 to 0.50 weak.

Table 10. Coefficient of Determination (R^2) Results

Endogenous Construct	R^2	Category
AI Support	0.274	Weak
Employee Performance	0.613	Moderate

Source: Researcher's Processed Data, 2026

Based on Table 10, an R^2 value of 0.613 for Employee Performance means that 61.3% of the variation in employee performance observed in this study can be jointly explained by Digital Competence, AI Support, and Organizational Support together with their interaction effect, while the remaining 38.7% is accounted for by factors outside the model, such as leadership, work culture, or compensation, which were not included in this study. This figure is classified as moderate and is reasonably strong for a social science model involving four predictor paths.

The R^2 value of 0.274 for AI Support indicates that Digital Competence, as the sole predictor of this construct within the model, explains only 27.4% of its variation, leaving 72.6% attributable to factors beyond the model, such as organizational policy on technology adoption, the availability of digital infrastructure, or leadership support. This value is classified as weak according to Hair et al., (2013), which is understandable given that AI Support in this model is explained by a single predictor rather than by a combination of predictors as in the case of Employee Performance.

Effect Size (f^2)

Beyond R^2 , the contribution of each exogenous construct to its corresponding endogenous construct was also examined separately through effect size (f^2), defined as the change in R^2 that occurs when a given exogenous construct is removed from the model. Cohen (1988) classifies a value of 0.02 as a small effect, 0.15 as medium, and 0.35 as large.

Table 11. Effect Size (f^2) Results

Path	f^2	Category
AI Support → Employee Performance	0.648	Large
Digital Competence → AI Support	0.378	Large
Digital Competence → Employee Performance	0.135	Small
Organizational Support → Employee Performance	0.035	Small
Interaction (OS × DC) → Employee Performance	0.041	Small

Source: Researcher's Processed Data, 2026

Based on Table 11, AI Support contributes a large effect to Employee Performance, as does Digital Competence to AI Support. In contrast, the direct paths from Digital Competence and Organizational Support to Employee Performance, along with the interaction effect, contribute only small effects. This pattern suggests that the model's explanatory strength rests more heavily on the pathway involving AI Support than on the direct or moderating pathways.

Predictive Relevance (Q^2)

The model's predictive relevance for out-of-sample data was tested through the blindfolding procedure developed by Stone (1974) and Geisser (1974), with a positive Q^2 value indicating that the model possesses adequate predictive capability.

Table 12. Predictive Relevance (Q^2) Results

Endogenous Construct	Q^2	Category
AI Support	0.212	Medium
Employee Performance	0.487	Large

Source: Researcher's Processed Data, 2026

Based on Table 12, both Q^2 values are positive, with Employee Performance reaching the large category and AI Support the medium category. The research model thus demonstrates good predictive relevance for both endogenous constructs.

Model Fit (SRMR)

Overall model fit was assessed through the Standardized Root Mean Square Residual (SRMR), which represents the discrepancy between the observed and model-implied correlations, with a threshold below 0.08 (Henseler et al., 2016).

Table 13. Model Fit Test Results

Model	SRMR	Threshold	Remark
Estimated Model	0.035	< 0.08	Fit

Source: Researcher's Processed Data, 2026

Based on Table 13, the SRMR value of 0.035 falls well below the required threshold, indicating that the research model fits the empirical data well.

Direct Effect Hypothesis Testing

The significance of each direct path coefficient was tested through a bootstrapping procedure with 5,000 resamples, applying a t-statistic above 1.96 and a p-value below 0.05 at a two-tailed 5% significance level (Hair et al., 2022).

Table 14. Direct Effect Hypothesis Testing Results

Path	β	t-statistic	p-value	Decision
Digital Competence → Employee Performance	0.275	4.827	0.000	H1 supported
Digital Competence → AI Support	0.524	10.951	0.000	H2 supported
AI Support → Employee Performance	0.592	12.428	0.000	H3 supported
Organizational Support → Employee Performance	-0.117	2.121	0.034	Significant (negative direction)

Source: Researcher's Processed Data, 2026

Based on Table 14, the three paths underlying H1, H2, and H3 are all significant and move in the hypothesized positive direction. The path from Organizational Support to Employee Performance is also significant, though in a negative direction contrary to the initial assumption. The interaction effect underlying H5 is presented separately in the moderation test in the following subsection.

Mediation Test

The mediating role of AI Support was tested through a bias-corrected bootstrap confidence interval as proposed by Preacher & Hayes (2008); the indirect effect is declared significant if the resulting 95% confidence interval does not cross zero.

Table 15. Indirect Effect Significance Test Results

Indirect Path	β	STDEV	t-statistic	p-value	95% BC CI
Digital Competence → AI Support → Employee Performance	0.310	0.039	8.042	0.000	[0.238 ; 0.389]

Source: Researcher's Processed Data, 2026

Based on Table 15, the confidence interval ranges from 0.238 to 0.389 and does not cross zero at any point, so the indirect effect of Digital Competence on Employee Performance through AI Support is declared significant, and H4 is supported by the data. To determine the type of mediation that occurred, the Variance Accounted For (VAF) was also calculated, defined as the proportion of the indirect effect relative to the total effect, following the categorization proposed by Hair et al., (2017): below 20% indicates no mediation, 20 to 80% indicates partial mediation, and above 80% indicates full mediation.

Table 16. Variance Accounted for (VAF) Calculation

Effect Component	β Value	Remark
Indirect effect	0.310	
Direct effect	0.275	

Total effect	0.585	0.310 + 0.275
VAF (indirect ÷ total)	53.0%	Partial mediation

Source: Researcher's Processed Data, 2026

Based on Table 16, a VAF value of 53.0% establishes AI Support as a partial mediator, rather than a full mediator, in the relationship between Digital Competence and Employee Performance. This means Digital Competence continues to affect Employee Performance directly, while a substantial share of that effect is also channeled through the strengthening of AI Support, with the two pathways contributing in a relatively balanced proportion

Moderation Test

The moderating role of Organizational Support on the direct relationship between Digital Competence and Employee Performance was tested through the product indicator approach, with the significance of the interaction coefficient assessed from a bootstrapping procedure with 5,000 resamples.

Table 17. Moderation Test Results

Interaction Path	β	STDEV	t-stat	p-value	95% BC CI
Organizational Support × Digital Competence → Employee Performance	0.127	0.050	2.549	0.011	[0.035 ; 0.226]

Source: Researcher's Processed Data, 2026

Based on Table 17, the interaction coefficient is significant and positive ($t = 2.549$; $p = 0.011$), meaning that the higher the Organizational Support perceived by employees, the stronger the effect of Digital Competence on Employee Performance. H5 is therefore supported by the data, although the moderating effect is classified as small in terms of effect size ($f^2 = 0.041$).

Steps to test your results here In this section, you should describe each step taken to complete your research. You should not include too many descriptive statistical results here; on the other hand, it should be summarized in a more readable table or graph. You should never forget the numbers for each table and chart presented in your paper.

DISCUSSION

Effect of Digital Competence on Employee Performance

The findings confirm that Digital Competence significantly and positively affects Employee Performance, supporting H1. Based on Social Exchange Theory (Cropanzano & Mitchell, 2005), digital competence represents a valuable personal resource that employees contribute to their organizations. Employees who can operate information systems, manage electronic data, and adapt to digital tools perform administrative tasks more efficiently and demonstrate greater initiative. These capabilities improve task and contextual performance, including service orientation and problem-solving (Koopmans et al., 2014).

This relationship is particularly important in Indonesia's digital government transformation under Presidential Regulation No. 95 of 2018 concerning the Electronic-Based Government System. In four Gorontalo City government

institutions—the Health Office, Population and Civil Registration Office, Investment and One-Stop Integrated Licensing Service Office, and Manpower, Cooperatives, and MSME Office—digital competence supports efficient administrative processes and quality public services.

The findings align with Sulaiman et al. (2025) and Ingsih et al. (2024), who also identified the importance of digital competence for employee performance and service quality. However, its direct effect is smaller than that of AI Support, indicating that digital skills alone may be insufficient. Therefore, the Gorontalo City Government should integrate digital competency training with appropriate AI-based systems to improve productivity, administrative efficiency, and public service delivery.

Effect of Digital Competence on AI Support

The findings confirm that Digital Competence has a significant and positive effect on AI Support, supporting H2, with a large effect size. According to Bandura's (1977) self-efficacy theory, digitally competent employees are more confident in understanding and using AI systems and are more likely to perceive them as beneficial. This finding aligns with the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003), which emphasizes the influence of individual abilities and experience on technology acceptance.

Previous studies support this relationship. Piotrowski and Revtiuk (2026) found that higher digital competence promotes positive perceptions of AI, while Giralaldi et al. (2024) demonstrated that technological proficiency influences public-sector employees' perceptions of AI usefulness. These findings indicate that digital competence shapes how employees perceive and utilize organizational AI systems. From the perspective of Social Exchange Theory, digitally competent employees are better able to recognize and use organizational resources, including AI support. Therefore, the effectiveness of AI support depends not only on the technology provided but also on employees' digital readiness. Local governments should integrate AI investments with digital literacy development programs to ensure that employees can effectively utilize AI systems and improve workplace performance.

Effect of AI Support on Employee Performance

The findings confirm that AI Support has a significant and positive effect on Employee Performance, representing the strongest relationship in the research model and supporting H3. AI systems improve efficiency by automating routine administrative tasks, reducing errors, and allowing employees to focus on complex decision-making and public service delivery. Consistent with Koopmans et al. (2014), AI support enhances task performance and reduces counterproductive work behavior.

From the perspective of Social Exchange Theory, employees who perceive AI systems as valuable organizational resources may reciprocate through improved performance. This finding aligns with Maulana et al. (2026) and Zhang and Yu (2025), who highlighted AI's contributions to employee performance and work adaptability. However, Li and Geng (2026) found that AI usage improved performance indirectly through AI self-efficacy and digital human resource

management practices. These differences may reflect variations in AI measurement and organizational contexts.

Despite its benefits, excessive reliance on AI may weaken employees' independent judgment if human capabilities are neglected. Therefore, local governments should integrate AI adoption with digital literacy development, critical thinking, and human decision-making. This balanced approach can maximize employee performance while maintaining public service quality.

The Mediating Role of AI Support in the Relationship Between Digital Competence and Employee Performance

The findings support H4, indicating that AI Support partially mediates the relationship between Digital Competence and Employee Performance. Digital competence improves performance directly through employees' ability to solve technical problems, adapt to system changes, and communicate effectively using digital channels. It also improves performance indirectly by strengthening the utilization of AI support.

According to Social Exchange Theory (Cropanzano & Mitchell, 2005), digital competence functions as a personal resource that contributes to performance while enabling employees to benefit from organizational technological resources. Both direct and indirect pathways remain important and complement each other. This finding aligns with Maulana et al. (2026), who identified AI adaptation as a mediator between digital competence and employee performance.

Practically, the Gorontalo City Government should integrate digital competency training with investments in AI systems. Developing digital skills without adequate technological support, or implementing AI without preparing employees to use it effectively, may limit performance improvements. Coordinating both strategies can enhance employee productivity, administrative efficiency, and public service quality.

Moderating Role of Organizational Support in the Relationship Between Digital Competence and Employee Performance

The findings support H5, showing that Organizational Support significantly strengthens the relationship between Digital Competence and Employee Performance. Employees who receive recognition, welfare support, and adequate resources are more likely to apply their digital skills effectively. According to Social Exchange Theory (Blau, 1964), employees reciprocate organizational support by contributing more effectively to organizational goals. Thus, organizational support facilitates the conversion of digital competence into improved performance.

These findings align with Wang et al. (2025), who highlighted the role of perceived organizational support in strengthening technology-related outcomes, and Chatterjee et al. (2023), who demonstrated the moderating role of digital leadership capability. Although the interaction effect is small, it remains theoretically and practically meaningful in complex organizational settings (Chin et al., 2003). Practically, the Gorontalo City Government should integrate digital skills training with employee recognition, welfare initiatives, and adequate work resources. Combining these measures can create a supportive workplace, help civil

servants apply digital competencies more effectively, improve employee performance, and enhance public service delivery.

Reversed Direct Effect of Organizational Support

The study found that Organizational Support has a significant negative direct effect on Employee Performance, contradicting conventional assumptions. However, this relationship was included as a structural component of the moderation analysis rather than an independently tested hypothesis, following Aiken and West (1991) and Dawson (2014). Therefore, the finding should be interpreted as exploratory rather than a rejection of organizational support theory. Previous studies report mixed results. Chaidir et al. (2025) identified a positive relationship between organizational support and employee performance, mediated by normative commitment, while Sameer (2022) found no significant relationship among public-sector managers in India. The present study extends this literature by identifying a negative direct effect.

Several factors may explain this result. Generalized organizational support may be ineffective when employees lack sufficient digital competence to use available resources productively. It may also encourage dependency and reduce individual initiative. Furthermore, differences in digital readiness among employees in institutions undergoing digital transformation may cause uniform support to benefit digitally competent employees while providing limited benefits to others. This interpretation aligns with H5, which demonstrates that organizational support strengthens the relationship between digital competence and employee performance. Practically, public institutions in Gorontalo City should assess employees' digital readiness and tailor organizational support to their specific needs. This targeted approach can improve resource allocation, strengthen digital competence, and enhance employee performance.

CONCLUSION AND RECOMMENDATION

The findings support all five hypotheses, confirming that Digital Competence positively influences Employee Performance and AI Support, while AI Support improves Employee Performance and partially mediates the relationship between Digital Competence and Employee Performance. Organizational Support significantly strengthens this relationship, although its direct effect on Employee Performance is negative, contrary to conventional expectations. These results demonstrate that digital competence and technological support are complementary resources, while the effectiveness of organizational support depends on employees' digital readiness.

The study contributes to Social Exchange Theory by extending its application to AI-mediated organizational relationships and providing empirical evidence from public service institutions in Gorontalo City, a medium-sized city undergoing digital transformation. Practically, government agencies should integrate digital competence development with stronger AI-based systems and tailor organizational support to employees' digital readiness, in accordance with Ministerial Regulation No. 6 of 2022. Future research should employ longitudinal designs, formally test moderated mediation models, expand samples across institutions and regions, and incorporate qualitative methods to investigate the

unexpected negative direct effect of Organizational Support on Employee Performance.

SUGGESTION

This study has several limitations. First, its cross-sectional design captures relationships at a single point in time and cannot establish causality or explain changes during digital transformation. Second, the use of self-reported data from a single source may introduce social desirability bias. Third, the sample is limited to four public service institutions in one medium-sized city, restricting the generalizability of the findings. Fourth, AI Support is measured through employees' perceptions rather than actual usage intensity. Finally, the model examines mediation and moderation separately without testing moderated mediation or incorporating other contextual factors, such as leadership style and organizational digital maturity. Future research should employ longitudinal or experimental designs, expand samples across institutions and regions, and measure AI utilization using objective behavioral or system-log data. Researchers should also test moderated mediation models and incorporate qualitative methods, particularly in-depth interviews, to better understand the unexpected negative direct effect of Organizational Support on Employee Performance.

ACKNOWLEDGMENT

The authors would like to express their gratitude to the Institute for Research and Community Service (LPPM) of Universitas Negeri Gorontalo for its funding support for this research under the Collaborative Research Scheme of the Faculty of Economics and Business, Universitas Negeri Gorontalo, based on Decree Number 648/UN47.B8/HK.04/2026 and Agreement/Contract Number 844/UN47.BB/KU/2026.

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