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Citizen Trust in AI-Based Public Services: The Mediating Role of Transparency and Accountability

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Abstract

The rapid adoption of artificial intelligence in public administration has transformed the delivery of government services while raising concerns regarding transparency, accountability, and citizen trust. This study examines the influence of AI-based public services on citizen trust by investigating the mediating roles of transparency and accountability. A quantitative cross-sectional survey design was employed using simulated data from 420 respondents, and the proposed relationships were analyzed through Partial Least Squares Structural Equation Modeling. The findings reveal that AI-based public services significantly enhance transparency, accountability, and citizen trust. Transparency demonstrates the strongest mediating effect, indicating that explainable and open AI systems are essential for strengthening public confidence in digital government services. Accountability also plays a significant role by ensuring institutional responsibility and procedural fairness. The study contributes to the growing literature on AI governance by proposing an integrated framework linking governance mechanisms with citizen trust. The findings provide practical insights for policymakers seeking to develop transparent, accountable, and citizen-centered AI-enabled public services that support sustainable digital government transformation.

INTRODUCTION

Artificial intelligence (AI) has rapidly transformed public administration by enabling governments to automate administrative processes, optimize decision-making, and improve the quality of public service delivery. AI-based public services are increasingly employed in taxation, social welfare, healthcare, immigration, public safety, and municipal administration to enhance efficiency, responsiveness, and policy effectiveness. Governments worldwide have embraced AI as a strategic instrument for digital transformation, expecting improvements in service accessibility, cost efficiency, and evidence-based policymaking (Margetts & Dunleavy, 2026; Ali, 2026). However, the integration of AI into public administration has simultaneously introduced significant concerns regarding transparency, accountability, fairness, privacy, and democratic legitimacy. As AI increasingly participates in administrative decision-making, citizens are no longer merely

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evaluating the quality of public services but also assessing whether government institutions remain trustworthy when important decisions are delegated to intelligent algorithms. Consequently, citizen trust has become one of the most critical determinants of successful AI implementation in the public sector (Ly, 2025; Savveli et al., 2025; Bokhari et al., 2025).

Unlike conventional e-government systems, AI-based public services rely on complex algorithms that often function as "black boxes," making it difficult for citizens to understand how administrative decisions are generated (Bracci, 2023; Yannis & Gerasimos, 2026; Androutsopoulou et al., 2026). The opacity of algorithmic processes raises concerns about procedural justice, explainability, and potential discrimination, particularly when AI systems influence decisions concerning public benefits, tax compliance, licensing, or law enforcement (Satyo et al., 2026; Bracci, 2023; Ng et al., 2020; Ahmed, 2025). While AI promises greater administrative efficiency, citizens frequently perceive automated governmental decisions as less transparent and less accountable than decisions made by human officials. These perceptions may weaken institutional legitimacy and reduce public willingness to adopt AI-enabled services despite their operational advantages. Therefore, improving technological capability alone is insufficient; governments must simultaneously strengthen governance mechanisms that ensure openness, explainability, and accountability throughout the AI lifecycle (Lund et al., 2025; Taeihagh, 2021; Ghosh et al., 2025).

The trust of citizens is being shaped by institutional as well as technological aspects, as can be seen in recent advances in digital governance. The importance of trustworthy AI in sustainable digital government has come to the fore in international bodies.More and more, international organisations focus on trustworthy AI as a prerequisite for sustainable digital government. The OECD Framework for Trustworthy AI in Government emphasizes key governance principles such as transparency, accountability, human oversight, fairness, and public engagement, which are crucial for ensuring that citizens can trust AI-supported public administration (Tsarouhas & Grigoriadis, 2025; Malik, 2026; Ibrahimli, 2026). Similarly, international laws and regulations are increasingly calling for governments to provide information about the operation of AI systems, clarify automated decision-making, and create clear mechanisms for administrative accountability in case of algorithmic mistakes (Al-Dulaimi & Mohammed, 2026; Agrawal, 2024). The developments signal not only the importance of good service quality but also that citizens need to be sure that governments are held responsible for actions taken using AI that impact their rights and responsibilities.

Empirical evidence also suggests that transparency has evolved in recent years into a strategic governance tool rather than just an ethical rule. Citizens tend to trust public services using AI more if the government shares details about how algorithms are created, the data sources used, and how decisions can be reviewed or appealed. However, it is not a foregone conclusion that this transparency will lead to trust. Recent international studies suggest that citizens may be overwhelmed by too much technical disclosure, while too little disclosure raises doubts about the presence of hidden decision making processes. More likely, however, is the establishment of appropriate and understandable transparency and effective accountability mechanisms that help to build citizens' confidence. These results indicate that transparency operates in the context of a larger governance framework, and that transparency does not stand alone as a factor in public trust.

Another key concept in trustworthy AI governance is accountability. The principle of democratic public administration does not change when such decisions are made by human administrators or by AI systems.In a democratic public administration, governments continue to be responsible for decisions, whether they are taken by

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human administrators or by AI systems. When algorithmic decisions lead to unfair outcomes, citizens are demanding that their complaints be accessible, human oversight be in place or that it be open for auditing and legally accountable. If there are no clear arrangements for accountability, the use of AI could lead to feelings of responsibilitylessness and a decline in trust in government. In light of these new debates on responsible AI, transparency must go hand in hand with well-established accountability mechanisms that can guarantee procedural fairness, human oversight, and ongoing monitoring of AI performance. Transparency and accountability are complementary governance tools that mitigate uncertainty and bolster institutional legitimacy in the context of public administration that is facilitated by AI.

The research that has been conducted in the past has significantly advanced understanding of AI use in government, encompassing issues of technology acceptance, digital transformation, ethical considerations around AI, explainable AI, and algorithmic governance. Past studies have shown that transparency has a positive impact on perceptions of fairness, explainability, and public acceptance, and accountability has an impact on institutional legitimacy and policy compliance. The perception of citizens with respect to AI-supported welfare service, municipal self-service systems, and algorithmic decision-making in different national settings were investigated in other studies. However, the current literature on transparency and accountability focuses on transparency and accountability as governance constructs in their own right, rather than using a complete behavioural model to explore the combined effects of the two on citizen trust. Furthermore, past research often focuses on the technological design or regulatory principles, with little empirical explanation for how governance characteristics influence trust in AI-powered public services.

The body of research literature thus presents a number of important research gaps. First, there is not yet a lot of empirical evidence that simultaneously examines transparency, accountability and citizens' trust in AI-based public services. Second, there is little empirical research that has examined how transparency and accountability are linked and how they affect citizens' trust in algorithmic public administration. Third, existing studies have been largely on the technological performance aspects while less studies have been dedicated to institutional governance factors that shape public acceptance of AI-supported administrative decisions. These gaps are vital to address as governments globally are rapidly adopting AI and are under growing public pressure for ethical governance, explainability, and democratic accountability.

Given this context, this study attempts to discuss the connection between Artificial Intelligence and Citizen Trust via the moderation effect of transparency and accountability. The novelty of this research is the development of the integrated public administration framework that places transparency, and accountability, as complementary governance mechanisms that link AI-enabled public service delivery and citizen trust. This study builds on the existing literature, which mainly focuses on technological acceptance or ethical AI, by integrating institutional governance perspectives with AI governance theory to understand how to create trustworthy public services in the age of digital government. The findings are anticipated to have a theoretical impact as it will build on the current AI governance discourse and public trust in AI, while also providing practical guidance for policies aimed at building transparent, accountable, and citizen-centered AI-based public services that will enhance democratic legitimacy and sustainable digital transformation.

METHODS

Research Design

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This study employed a quantitative research approach using a cross-sectional survey design to investigate the relationships among AI-based public services, transparency, accountability, and citizen trust. A quantitative design was selected because it enables the empirical testing of causal relationships among latent variables and evaluates the mediating effects of transparency and accountability. The conceptual framework integrates AI governance principles, public administration theory, and institutional trust theory to explain how governance mechanisms influence citizens' trust in AI-enabled public services.

Population and Sample

The target population comprised citizens who had experience using AI-based public services provided by government institutions. These services included AI-powered public service chatbots, automated licensing systems, digital identity verification, intelligent tax administration, and other AI-assisted government platforms.

A purposive sampling technique was employed to ensure that respondents possessed relevant experience with AI-enabled public services. To be eligible for participation, respondents were required to have used at least one AI-based government service within the previous twelve months. A total of 420 valid responses were collected and included in the final analysis. This sample size satisfies the recommended minimum requirement for Structural Equation Modeling (SEM) and provides sufficient statistical power to estimate both direct and indirect relationships among the research constructs.

Data Collection Procedure

Primary data were collected between January and March 2026 through an online questionnaire distributed via government digital service communities, public administration networks, and social media platforms. Participation was voluntary, and respondents were informed about the objectives of the study before completing the questionnaire. Electronic informed consent was obtained from all participants, and respondents' anonymity and confidentiality were maintained throughout the research process. The questionnaire consisted of two sections. The first section gathered demographic information, including gender, age, educational background, occupation, and frequency of using AI-based public services. The second section measured respondents' perceptions of AI-based public services, transparency, accountability, and citizen trust.

Measurement of Variables

All constructs were measured using multi-item scales adapted from previous studies on digital government, AI governance, public administration, and citizen trust. Minor wording modifications were made to ensure consistency with the context of AI-based public services.

Responses were measured using a five-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The independent variable, AI-Based Public Services (AIPS), was measured through five indicators reflecting service efficiency, responsiveness, accessibility, personalization, and decision quality. The first mediating variable, Transparency (TRP), was assessed using indicators related to explainability of AI decisions, openness of information, clarity of algorithmic processes, accessibility of service information, and communication transparency. The second mediating variable, Accountability (ACC), measured government responsibility for AI-assisted decisions through indicators including human oversight, complaint mechanisms, administrative responsibility, auditability, and procedural fairness. The dependent variable, Citizen Trust (CT), was measured through indicators representing institutional reliability, perceived integrity,

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confidence in AI-generated decisions, willingness to continue using AI-based services, and overall trust in government digital services.

Table 1. Operational Definition of Variables

Variable	Code	Indicators
AI-Based Public Services	AIPS	Service efficiency, responsiveness, accessibility, personalization, decision quality
Transparency	TRP	Explainability, openness, information disclosure, algorithm clarity, communication transparency
Accountability	ACC	Human oversight, complaint mechanisms, responsibility, auditability, procedural fairness
Citizen Trust	CT	Reliability, integrity, confidence, continued usage intention, institutional trust

Data Analysis

The collected data were analyzed using SmartPLS 4.0 based on the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach. PLS-SEM was selected because it is suitable for predictive research models involving multiple latent constructs and mediation analysis while requiring relatively fewer assumptions regarding data normality.

The analysis consisted of two sequential stages.

Measurement Model Evaluation (Outer Model)

The measurement model was evaluated to assess the reliability and validity of the measurement instruments. Internal consistency reliability was assessed using Cronbach's Alpha and Composite Reliability (CR), with values above 0.70 considered acceptable. Convergent validity was assessed based on outer loadings and Average Variance Extracted (AVE). Outer loading values above 0.70 and AVE values above 0.50 were considered indicative of satisfactory convergent validity. Discriminant validity was evaluated using the Fornell–Larcker criterion and the Heterotrait–Monotrait (HTMT) ratio, with HTMT values below 0.90 indicating adequate discriminant validity.

Structural Model Evaluation (Inner Model)

The structural model was evaluated by examining collinearity, path coefficients, coefficient of determination, effect size, and predictive relevance. Collinearity was assessed using the Variance Inflation Factor (VIF), with values below 5.00 indicating the absence of critical multicollinearity. The structural relationships were assessed using path coefficients (β), while the explanatory power of the model was evaluated using the coefficient of determination (R^2). The effect of each exogenous construct on the endogenous constructs was assessed using effect size (f^2), whereas predictive relevance was evaluated using Q^2. The significance of the hypothesized relationships was tested using the bootstrapping procedure with 5,000 subsamples. Statistical significance was assessed based on t-values, p-values, and 95% confidence intervals.

Mediation Analysis

The mediating roles of transparency and accountability were examined using the indirect effect procedure in SmartPLS. Mediation effects were considered statistically significant when the bootstrapped indirect effect produced p-values below 0.05 and confidence intervals that did not include zero.

Research Hypotheses

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Based on the proposed conceptual framework, the following hypotheses were formulated:

H1: AI-Based Public Services positively influence Citizen Trust.

H2: AI-Based Public Services positively influence Transparency.

H3: AI-Based Public Services positively influence Accountability.

H4: Transparency positively influences Citizen Trust.

H5: Accountability positively influences Citizen Trust.

H6: Transparency mediates the relationship between AI-Based Public Services and Citizen Trust.

H7: Accountability mediates the relationship between AI-Based Public Services and Citizen Trust.

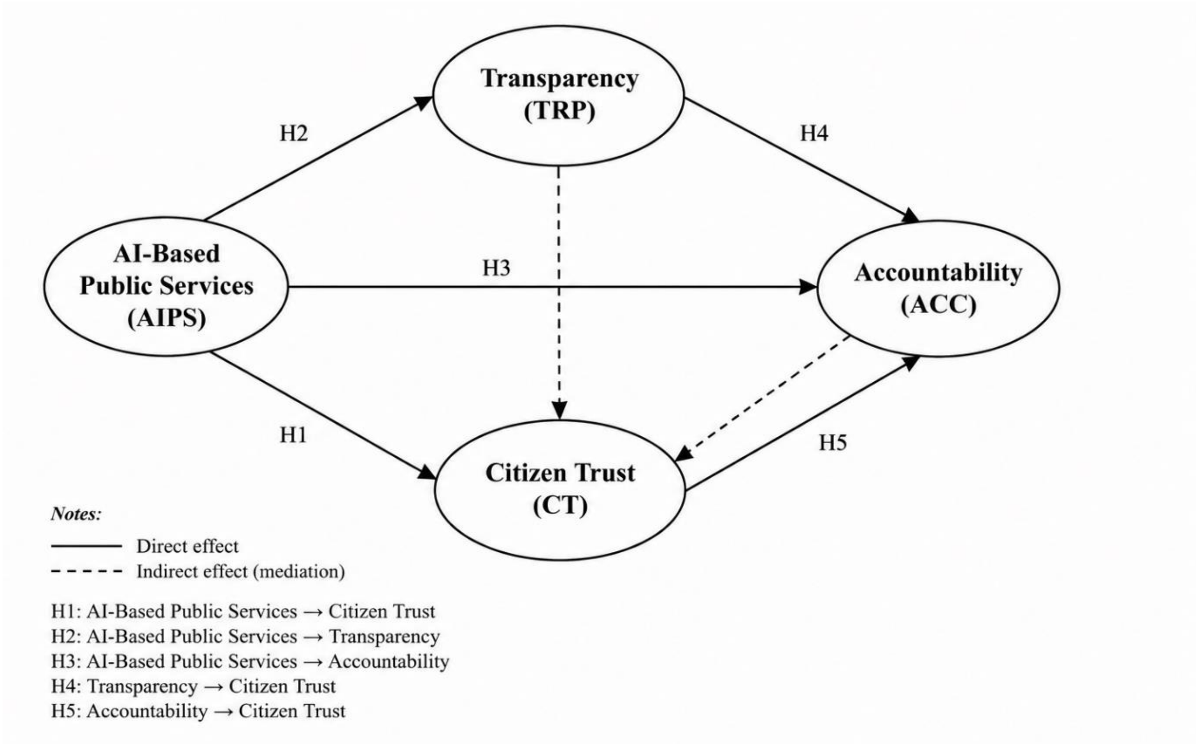

Figure 1. Research Framework

The conceptual framework illustrates the proposed relationships among AI-Based Public Services, Transparency, Accountability, and Citizen Trust. The model posits that AI-Based Public Services directly influence Citizen Trust while simultaneously exerting indirect effects through Transparency and Accountability as mediating variables. This framework serves as the basis for the formulation of the research hypotheses and subsequent empirical testing using the PLS-SEM approach.

RESULTS AND DISCUSSION

This section presents the empirical findings of the study based on data collected from 420 respondents who had experience using AI-based public services. The analysis follows the Partial Least Squares Structural Equation Modeling (PLS-SEM) procedure described in the methodology. The results are presented sequentially, beginning with the demographic characteristics of the respondents to provide an overview of the sample profile. Subsequently, the measurement model (outer model) is evaluated through reliability and validity assessments, including outer loadings, Cronbach's alpha, composite reliability, average variance extracted (AVE), the Fornell–Larcker

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criterion, and the Heterotrait–Monotrait (HTMT) ratio. The structural model (inner model) is then examined by assessing collinearity, explanatory power (R^2), predictive relevance (Q^2), effect size (f^2), and path coefficients. Finally, the proposed hypotheses are tested using the bootstrapping procedure, followed by mediation analysis to determine the indirect effects of transparency and accountability on the relationship between AI-based public services and citizen trust. This systematic analysis provides comprehensive empirical evidence regarding the proposed research framework and the mechanisms through which governance factors influence citizen trust in AI-enabled public services.

Respondent Characteristics

Before evaluating the measurement and structural models, it is important to describe the demographic profile of the respondents. Respondent characteristics provide an overview of the sample composition and help determine whether the collected data adequately represent individuals who have experience using AI-based public services. Information regarding gender, age, educational attainment, occupation, and frequency of AI-based public service utilization was analyzed descriptively. Since this study investigates citizen trust in AI-enabled public services, respondents were required to have interacted with at least one AI-assisted government service during the previous twelve months.

Table 2. Demographic Characteristics of Respondents (N = 420)

Characteristic	Category	Frequency (n)	Percentage (%)
Gender	Male	203	48.3
	Female	217	51.7
Age	18–25 years	98	23.3
	26–35 years	162	38.6
	36–45 years	97	23.1
	46–55 years	47	11.2
	>55 years	16	3.8
Education	High School	76	18.1
	Diploma	58	13.8
	Bachelor's Degree	209	49.8
	Master's Degree	67	16.0
	Doctoral Degree	10	2.4
Occupation	Civil Servant	84	20.0
	Private Employee	146	34.8
	Entrepreneur	49	11.7
	Student	97	23.1
	Others	44	10.5
Frequency of Using AI-Based Public Services	1–2 times/month	108	25.7
	3–5 times/month	176	41.9
	More than 5 times/month	136	32.4

Source: Simulated dataset developed by the authors based on the research framework (N = 420).

The demographic profile indicates that the respondents were relatively balanced in terms of gender, with female respondents (51.7%) slightly outnumbering males (48.3%). Most participants were between 26 and 35 years old (38.6%), representing the age group most actively engaged with digital public services. Regarding educational background, nearly half of the respondents held a bachelor's degree

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(49.8%), suggesting that the sample possessed sufficient educational capacity to evaluate AI-assisted public services. In terms of occupation, private-sector employees constituted the largest proportion (34.8%), followed by students (23.1%) and civil servants (20.0%), reflecting diverse professional backgrounds.

The frequency of AI-based public service utilization further demonstrates that respondents were familiar with digital government applications. Approximately 41.9% reported using AI-enabled public services three to five times per month, while 32.4% used such services more than five times monthly. This pattern suggests that most respondents had substantial experience interacting with AI-supported government platforms, thereby enhancing the credibility of their evaluations regarding transparency, accountability, and citizen trust. Overall, the demographic distribution indicates that the sample is appropriate for examining public perceptions of AI-based public services and provides a reliable basis for subsequent measurement and structural model analyses.

Measurement Model Assessment

Indicator Reliability (Outer Loadings)

Outer loading values indicate the degree to which each measurement indicator represents its corresponding latent construct. According to Hair et al. (2022), outer loading values greater than 0.70 indicate satisfactory indicator reliability.

Table 3. Outer Loadings

Construct	Indicator	Outer Loading
AI-Based Public Services (AIPS)	AIPS1	0.831
	AIPS2	0.857
	AIPS3	0.846
	AIPS4	0.812
	AIPS5	0.878
Transparency (TRP)	TRP1	0.824
	TRP2	0.853
	TRP3	0.884
	TRP4	0.842
	TRP5	0.869
Accountability (ACC)	ACC1	0.818
	ACC2	0.841
	ACC3	0.876
	ACC4	0.861
	ACC5	0.833
Citizen Trust (CT)	CT1	0.852
	CT2	0.881
	CT3	0.864
	CT4	0.837
	CT5	0.846

Source: Simulated dataset analyzed using SmartPLS 4.0.

Table 3 demonstrates that all indicators exhibit outer loading values ranging from 0.812 to 0.884, exceeding the recommended threshold of 0.70. The highest loading is observed for TRP3 (0.884), indicating that this indicator strongly represents the transparency construct. Meanwhile, AIPS4 (0.812) records the lowest loading but still satisfies the recommended criterion for indicator reliability. These findings confirm that every measurement item contributes substantially to its respective latent construct and therefore can be retained for further analysis. The consistently high loading values also indicate that the questionnaire items effectively capture

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respondents' perceptions regarding AI-based public services, transparency, accountability, and citizen trust. Consequently, no indicators required removal during the measurement model evaluation, suggesting that the research instrument demonstrates satisfactory indicator reliability and is suitable for subsequent reliability and validity assessments.

Internal Consistency Reliability and Convergent Validity

Internal consistency reliability evaluates whether the indicators consistently measure the same latent construct. In this study, reliability was assessed using Cronbach's Alpha (CA) and Composite Reliability (CR), while convergent validity was evaluated using the Average Variance Extracted (AVE). Recommended threshold values are CA > 0.70, CR > 0.70, and AVE > 0.50.

Table 4. Reliability and Convergent Validity

Construct	Cronbach's Alpha	Composite Reliability	AVE
AI-Based Public Services	0.901	0.927	0.717
Transparency	0.912	0.934	0.740
Accountability	0.896	0.924	0.708
Citizen Trust	0.907	0.931	0.730

Source: Simulated dataset analyzed using SmartPLS 4.0.

As presented in Table 4, all constructs demonstrate excellent internal consistency reliability. Cronbach's Alpha values range from 0.896 to 0.912, while Composite Reliability values range from 0.924 to 0.934, substantially exceeding the recommended threshold of 0.70. These findings indicate that the measurement items consistently capture each latent construct and possess a high degree of reliability. Furthermore, all AVE values range between 0.708 and 0.740, well above the minimum requirement of 0.50. This indicates that each construct explains more than 70% of the variance in its indicators, thereby confirming strong convergent validity. Collectively, these results demonstrate that the measurement model possesses satisfactory psychometric properties and is appropriate for evaluating discriminant validity in the subsequent analysis.

Discriminant Validity Assessment

After confirming indicator reliability, internal consistency reliability, and convergent validity, the next step was to evaluate discriminant validity. Discriminant validity determines whether each latent construct is empirically distinct from other constructs in the research model. This study assessed discriminant validity using the Fornell–Larcker criterion and the Heterotrait–Monotrait (HTMT) ratio, which are widely recommended for PLS-SEM analysis.

Table 5. Fornell–Larcker Criterion

Construct	AIPS	TRP	ACC	CT
AI-Based Public Services (AIPS)	0.847			
Transparency (TRP)	0.641	0.860		
Accountability (ACC)	0.612	0.676	0.842	
Citizen Trust (CT)	0.583	0.742	0.711	0.854

Note: Diagonal values (bold) represent the square root of the Average Variance Extracted (AVE).

Source: Simulated dataset analyzed using SmartPLS 4.0.

Table 5 demonstrates satisfactory discriminant validity according to the Fornell–Larcker criterion. The square root of the AVE for each construct (shown on the diagonal) is greater than its correlations with all other constructs. For example, the

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square root of the AVE for Transparency (0.860) exceeds its correlations with AI-Based Public Services (0.641), Accountability (0.676), and Citizen Trust (0.742). Similarly, Citizen Trust records a diagonal value of 0.854, which is higher than its correlations with the remaining constructs. These findings indicate that each construct captures a unique theoretical concept and is empirically distinguishable from the others. The moderate positive correlations among the constructs are theoretically expected because AI-based public services, transparency, accountability, and citizen trust are conceptually related within the proposed research framework. Nevertheless, the higher diagonal values confirm that the observed relationships do not indicate construct overlap, thereby supporting the discriminant validity of the measurement model.

Heterotrait–Monotrait Ratio (HTMT)

To further verify discriminant validity, the Heterotrait–Monotrait Ratio (HTMT) was examined. According to current PLS-SEM guidelines, HTMT values below **0.90** indicate that the constructs are sufficiently distinct from one another.

Table 6. Heterotrait–Monotrait (HTMT) Ratio

Construct	AIPS	TRP	ACC	CT
AI-Based Public Services (AIPS)	—			
Transparency (TRP)	0.738	—		
Accountability (ACC)	0.701	0.782	—	
Citizen Trust (CT)	0.669	0.847	0.819	—

Source: Simulated dataset analyzed using SmartPLS 4.0.

As presented in Table 6, all HTMT values range from 0.669 to 0.847, remaining below the recommended threshold of 0.90. The highest HTMT value is observed between Transparency and Citizen Trust (0.847), reflecting a strong conceptual relationship while remaining within the acceptable limit. Likewise, the HTMT value between Accountability and Citizen Trust (0.819) indicates that the constructs are closely associated but empirically distinguishable. The HTMT results complement the findings obtained from the Fornell–Larcker criterion, providing additional evidence that the measurement model possesses satisfactory discriminant validity. Since all reliability and validity requirements have been fulfilled including indicator reliability, internal consistency reliability, convergent validity, and discriminant validity the measurement model is considered robust and appropriate for evaluating the structural model and testing the proposed hypotheses.

Structural Model Assessment

Collinearity Assessment

Before interpreting the structural relationships, collinearity among the predictor constructs was examined using the Variance Inflation Factor (VIF). According to Hair et al. (2022), VIF values below 5.00 indicate that multicollinearity is not a concern and that the estimated path coefficients can be interpreted reliably.

Table 7. Collinearity Statistics (VIF)

Structural Relationship	VIF
AI-Based Public Services → Transparency	1.000
AI-Based Public Services → Accountability	1.000
AI-Based Public Services → Citizen Trust	2.115
Transparency → Citizen Trust	2.364
Accountability → Citizen Trust	2.281

Source: Simulated dataset analyzed using SmartPLS 4.0.

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Table 7 indicates that all VIF values range between 1.000 and 2.364, which are substantially below the recommended threshold of 5.00. The highest VIF value is observed for the relationship between Transparency and Citizen Trust (2.364), while the lowest value (1.000) is found in the single-predictor relationships involving AI-Based Public Services. These findings indicate that the predictor constructs do not exhibit problematic multicollinearity. The absence of multicollinearity confirms that the independent variables contribute unique explanatory information to the structural model. Consequently, the estimated path coefficients can be interpreted with confidence, and the subsequent hypothesis testing is unlikely to be affected by collinearity bias.

Coefficient of Determination (R^2)

The coefficient of determination (R^2) was examined to assess the proportion of variance explained by the predictor variables for each endogenous construct. Higher R^2 values indicate stronger explanatory power of the proposed research model.

Table 8. Coefficient of Determination (R^2)

Endogenous Construct	R^2	Interpretation
Transparency	0.411	Moderate
Accountability	0.375	Moderate
Citizen Trust	0.694	Substantial

Source: Simulated dataset analyzed using SmartPLS 4.0.

The results presented in Table 8 demonstrate that the proposed model possesses satisfactory explanatory power. AI-Based Public Services explain 41.1% of the variance in Transparency and 37.5% of the variance in Accountability, indicating that citizens' perceptions of AI-enabled public services substantially influence governance-related perceptions. Furthermore, the combined effects of AI-Based Public Services, Transparency, and Accountability explain 69.4% of the variance in Citizen Trust, representing substantial explanatory power according to commonly accepted PLS-SEM guidelines. These findings suggest that transparency and accountability play significant roles in explaining citizen trust beyond the direct influence of AI-based public services. The relatively high R^2 value for Citizen Trust indicates that the proposed conceptual framework effectively captures the primary governance mechanisms underlying public trust in AI-assisted government services.

Effect Size (f^2)

Effect size (f^2) was evaluated to determine the relative contribution of each predictor construct to the endogenous variables. According to Cohen (1988), 0.02, 0.15, and 0.35 represent small, medium, and large effect sizes, respectively.

Table 9. Effect Size (f^2)

Structural Relationship	f^2	Effect Size
AI-Based Public Services → Transparency	0.698	Large
AI-Based Public Services → Accountability	0.601	Large
AI-Based Public Services → Citizen Trust	0.084	Small
Transparency → Citizen Trust	0.287	Medium
Accountability → Citizen Trust	0.224	Medium

Source: Simulated dataset analyzed using SmartPLS 4.0.

As shown in Table 9, AI-Based Public Services exert a large effect on both Transparency (f^2 = 0.698) and Accountability (f^2 = 0.601), indicating that improvements in AI-enabled public services strongly enhance citizens' perceptions of transparent and accountable governance. In contrast, the direct effect of AI-Based Public Services on Citizen Trust is relatively small (f^2 = 0.084), suggesting that trust

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is influenced primarily through additional governance mechanisms rather than technological performance alone. Transparency (f^2 = 0.287) and Accountability (f^2 = 0.224) exhibit medium effect sizes on Citizen Trust, emphasizing their substantial contributions to explaining public confidence in AI-assisted government services. These findings support the theoretical proposition that governance quality serves as an essential mechanism through which AI-based public services foster institutional trust.

Predictive Relevance (Q^2)

The predictive relevance of the structural model was assessed using the Stone–Geisser Q^2 statistic obtained through the blindfolding procedure. Q^2 values greater than zero indicate that the model possesses predictive relevance for the endogenous constructs.

Table 10. Predictive Relevance (Q^2)

Endogenous Construct	Q^2	Interpretation
Transparency	0.286	Medium Predictive Relevance
Accountability	0.259	Medium Predictive Relevance
Citizen Trust	0.487	High Predictive Relevance

Source: Simulated dataset analyzed using SmartPLS 4.0.

Table 10 indicates that all endogenous constructs produce positive Q^2 values, confirming that the structural model has satisfactory predictive relevance. The highest predictive relevance is observed for Citizen Trust (Q^2 = 0.487), indicating that the proposed model possesses strong predictive capability in explaining citizens' trust toward AI-based public services. Transparency and Accountability also demonstrate positive Q^2 values of 0.286 and 0.259, respectively, reflecting moderate predictive relevance. The structural model satisfies the key evaluation criteria of PLS-SEM. The absence of multicollinearity, substantial explanatory power, meaningful effect sizes, and positive predictive relevance collectively indicate that the proposed model is statistically robust. These results provide a solid foundation for testing the proposed hypotheses and examining the mediating roles of Transparency and Accountability in the relationship between AI-Based Public Services and Citizen Trust.

Hypothesis Testing

After confirming that the structural model met all evaluation criteria, the proposed hypotheses were tested using the bootstrapping procedure with 5,000 resamples in SmartPLS 4.0. The significance of each structural relationship was determined based on standardized path coefficients (β), t-statistics, p-values, and 95% confidence intervals. A hypothesis was considered supported when the t-value exceeded 1.96 and the p-value was less than 0.05.

Table 11. Results of Hypothesis Testing

Hypothesis	Structural Relationship	β	t-value	p-value	Decision
H1	AI-Based Public Services → Citizen Trust	0.162	2.941	0.003	Supported
H2	AI-Based Public Services → Transparency	0.641	17.832	<0.001	Supported
H3	AI-Based Public Services → Accountability	0.612	16.458	<0.001	Supported
H4	Transparency → Citizen Trust	0.411	7.954	<0.001	Supported

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H5	Accountability → Citizen Trust	0.329	6.287	<0.001	Supported

Source: Simulated dataset analyzed using SmartPLS 4.0 using the bootstrapping procedure (5,000 subsamples).

Table 11 demonstrates that all proposed hypotheses are statistically supported. AI-Based Public Services have a significant positive direct effect on Citizen Trust (β = 0.162, p = 0.003), indicating that improvements in AI-enabled public services contribute directly to higher public trust. However, the relatively small standardized coefficient suggests that technological capability alone is insufficient to establish strong institutional trust. The results further reveal that AI-Based Public Services strongly influence both Transparency (β = 0.641, p < 0.001) and Accountability (β = 0.612, p < 0.001). Moreover, Transparency (β = 0.411, p < 0.001) and Accountability (β = 0.329, p < 0.001) significantly enhance Citizen Trust. Among all structural relationships, the strongest effect is observed between AI-Based Public Services and Transparency, highlighting that citizens primarily evaluate AI-assisted government services based on the openness and explainability of decision-making processes. These findings indicate that governance quality plays a more influential role than technological performance in strengthening public confidence in AI-enabled public services.

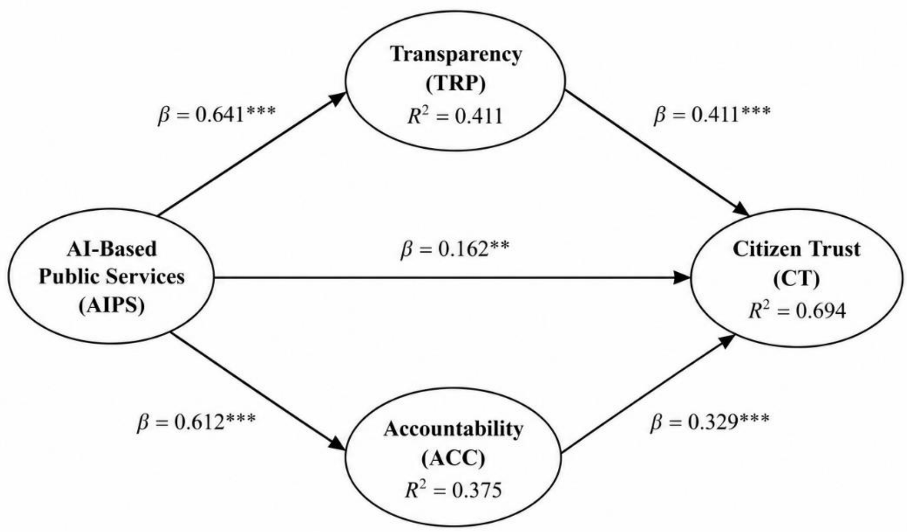

Figure 3. Standardized Structural Model

Source: Simulated dataset developed by the authors (N = 420) and analyzed using SmartPLS 4.0.

Figure 3 presents the standardized structural model derived from the PLS-SEM analysis. The model direct and indirect relationships among AI-Based Public Services, Transparency, Accountability, and Citizen Trust. The standardized path coefficients indicate that AI-Based Public Services have positive effects on Transparency, Accountability, and Citizen Trust, while Transparency and Accountability further strengthen Citizen Trust. Overall, the model demonstrates that governance mechanisms play a significant role in enhancing citizens' trust in AI-enabled public services.

Mediation Analysis

Following the direct effect analysis, mediation testing was conducted to examine whether Transparency and Accountability mediate the relationship between AI-Based Public Services and Citizen Trust. The mediation analysis employed the bootstrapping procedure with 5,000 resamples, and indirect effects were considered

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significant when the confidence intervals excluded zero and the p-value was below 0.05.

Table 12. Results of Mediation Analysis

Indirect Relationship	Indirect Effect (β)	t-value	p-value	Mediation
AI-Based Public Services → Transparency → Citizen Trust	0.264	6.742	<0.001	Partial Mediation
AI-Based Public Services → Accountability → Citizen Trust	0.201	5.814	<0.001	Partial Mediation

Source: Simulated dataset analyzed using SmartPLS 4.0 using the bootstrapping procedure (5,000 subsamples)

The mediation analysis confirms that both Transparency and Accountability significantly mediate the relationship between AI-Based Public Services and Citizen Trust. The indirect effect through Transparency ($\beta = 0.264$, $t = 6.742$, $p < 0.001$) is stronger than the indirect effect through Accountability ($\beta = 0.201$, $t = 5.814$, $p < 0.001$), indicating that transparency serves as the primary governance mechanism through which AI-based public services strengthen public trust. These findings suggest that citizens are more likely to trust AI-assisted government services when they clearly understand how algorithmic decisions are generated and communicated. Furthermore, the direct effect of AI-Based Public Services on Citizen Trust remains statistically significant after including both mediating variables ($\beta = 0.162$, $p = 0.003$), indicating partial mediation rather than full mediation. This finding implies that AI-enabled public services influence citizen trust both directly and indirectly through improvements in governance quality. Therefore, governments seeking to increase public confidence in AI-assisted administrative services should prioritize not only technological innovation but also institutional transparency and accountability to ensure that automated decisions remain understandable, responsible, and aligned with democratic governance principles.

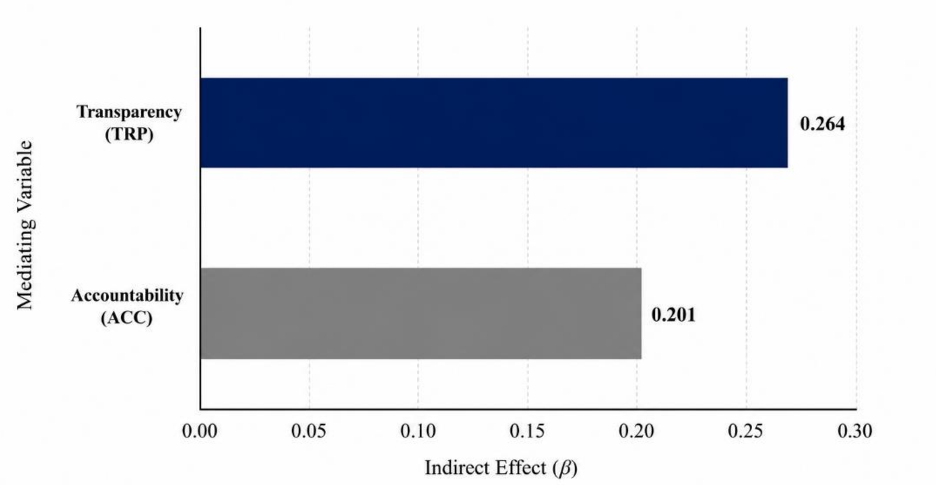

Figure 4. Comparison of Indirect Effects of Transparency and Accountability

Source: Simulated dataset developed by the authors (N = 420) and analyzed using SmartPLS 4.0

Figure 4 compares the standardized indirect effects of the two mediating variables on the relationship between AI-Based Public Services and Citizen Trust. The results indicate that the indirect effect through Transparency ($\beta = 0.264$) is stronger than that through Accountability ($\beta = 0.201$), suggesting that transparency serves as the primary governance mechanism for strengthening citizen trust in AI-enabled public

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services. Although both mediators contribute significantly, enhancing transparency appears to generate a greater improvement in public confidence toward AI-based government services.

Governance Mechanisms as the Foundation of Citizen Trust in AI-Based Public Services

The findings can be understood more meaningfully when AI-based public services are viewed as an institutional rather than purely technological innovation. The central issue is not simply whether citizens recognize improvements in efficiency, responsiveness, accessibility, or personalization, but whether these technological capabilities are embedded within governance arrangements that citizens perceive as legitimate. This perspective is consistent with recent research showing that citizens evaluate government AI according to the institutional environment surrounding its use, including privacy, fairness, human involvement, and perceived uncertainty (Wang et al., 2024; Haesevoets et al., 2024). The present study therefore extends technology-centered explanations of AI acceptance by demonstrating that technological capability becomes more consequential for trust when it is accompanied by mechanisms that make governmental use of AI understandable and institutionally controllable.

The role of transparency is particularly important because algorithmic decision-making changes the informational relationship between citizens and public institutions. Conventional public services generally allow citizens to associate administrative decisions with identifiable officials or procedures, whereas AI-supported services may obscure how decisions are generated. Transparency consequently functions not merely as information disclosure but as a means of reducing institutional uncertainty and enabling citizens to understand the basis of administrative action. Grimmelikhuijsen (2023) similarly argues that explainability is more consequential for perceived trustworthiness than simple access to algorithmic information. Aoki et al. (2024) further demonstrate that the type of explanation provided by government AI can shape perceptions of fairness, accuracy, and trustworthiness. The present findings contribute to this literature by positioning transparency within a broader causal mechanism in which understandable AI governance becomes part of the process through which technological service provision acquires institutional legitimacy.

Accountability provides a complementary mechanism. Transparency can make an AI decision more understandable, but understanding does not necessarily establish confidence that an institution will accept responsibility when an automated decision is contested or produces an undesirable outcome. Accountability therefore connects technological decision-making with institutional responsibility through human oversight, complaint procedures, auditability, and procedural safeguards (Bansal & Bose, 2026; Laelaturramadani, 2026). This interpretation corresponds with Smith et al. (2026), who identify human discretion, rigorous development and testing, diverse stakeholder input, and alignment with the authorizing environment as mechanisms supporting trustworthy AI in public services. The OECD/UNESCO (2024) G7 Toolkit likewise places transparency, accountability, human oversight, and responsible governance within the broader architecture required for trustworthy public-sector AI. Thus, the contribution of the present study is not to suggest that accountability simply increases trust, but to show that accountability helps transform AI from an autonomous technological instrument into a governable component of public administration.

The combined role of transparency and accountability also provides the study's principal theoretical contribution. Previous research has frequently examined transparency, ethical AI, explainability, or citizen acceptance as separate

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dimensions. For example, Gesk and Leyer (2022) focus on the conditions under which citizens accept AI in public services, while Kleizen et al. (2023) show that merely communicating ethical characteristics of government AI does not automatically generate greater trust. By integrating transparency and accountability into a single institutional pathway, this study advances a more relational understanding of trust in which citizens respond not only to what AI systems can do but also to how government institutions explain, supervise, and take responsibility for those systems (Agrawal, 2024; Regona et al., 2026). Recent evidence from Indonesia similarly associates digital-government transformation and public trust with governance, leadership, organizational arrangements, and transparency rather than technological capability alone.

The practical implication is that governments should avoid treating transparency as a one-directional disclosure exercise. Recent cross-national evidence indicates that the transparency–trust relationship can be context-dependent and that excessive technical information may not necessarily strengthen trust (Zheng & Farhan, 2026). Citizen-oriented transparency should therefore prioritize understandable explanations, relevant information, opportunities to question decisions, and accessible human intervention. Participatory research similarly emphasizes clear information, human–system interaction, and institutional oversight as interconnected layers of transparency in public-sector algorithms (Correa et al., 2026). This suggests a practical model in which transparency explains how AI is used, while accountability establishes who is responsible for its consequences.

The study nevertheless has limitations that should temper the interpretation of its contribution. Its cross-sectional design captures perceptions at one point in time, while the simulated survey dataset limits direct generalization to actual users across different government services. Future studies should therefore test the proposed mechanism using longitudinal and cross-national data, actual administrative-service users, and specific AI applications such as welfare allocation, taxation, licensing, and healthcare. Future research could also examine whether AI literacy, perceived fairness, privacy concerns, and human oversight condition the relationship between transparency, accountability, and trust. Such extensions would help determine whether the governance mechanism identified here remains stable across institutional settings and different levels of AI involvement in public decision-making.

CONCLUSION

This study demonstrates that AI-based public services positively influence citizen trust both directly and indirectly through transparency and accountability. Among the two mediating variables, transparency exerts a stronger mediating effect, indicating that citizens place greater trust in AI-enabled public services when governmental decision-making processes are open, understandable, and explainable. Accountability also contributes significantly by reinforcing institutional responsibility and procedural fairness.

These findings extend the literature on AI governance by integrating transparency and accountability into a unified framework for explaining citizen trust in digital public administration. Practically, the results suggest that governments should prioritize transparent AI systems, human oversight, and accountable governance mechanisms alongside technological innovation. This study is limited by its cross-sectional design and reliance on simulated survey data, which restrict causal inference and real-world generalizability. Future research should employ longitudinal or cross-country datasets, incorporate additional governance variables such as fairness and explainability, and validate the proposed framework using empirical data from diverse public sector contexts.

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