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Technological Readiness as a Driver of Artificial Intelligence Adoption in Public Administration and Auditing: Serial Mediation by Perceived Ease of Use and Perceived Usefulness

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Abstract

The purpose of this study is to explore the impact of technological readiness on public employees' AI adoption, considering the serial mediating roles of perceived ease of use and perceived usefulness. Data were collected from 409 public employees in Türkiye who voluntarily participated in the study through an online survey. The obtained data were analyzed using IBM SPSS Statistics, IBM SPSS AMOS, and PROCESS Macro v4.2. The findings reveal that technological readiness directly and significantly affects AI adoption. Furthermore, the results show that perceived ease of use and perceived usefulness play a serial multiple mediating role in this relationship. The findings suggest that strengthening public employees' perceptions of technology, especially perceived ease of use and usefulness, is critical for increasing AI adoption in public administration and auditing. In this respect, the study contributes to the development of strategies for the effective implementation of AI applications and to transformation policies that center on employees' perceptions of technology.

Key words: Public Administration, Public Auditing, AI Adoption, Technology Readiness, Technology Adoption Model
JEL Code: H83, M15, M42

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1. Introduction

Artificial Intelligence (AI), as a stage of digitalization, is reshaping the phenomenon of public administration worldwide and creates a transformative potential, especially in areas such as public administration and auditing. Today, public institutions are increasingly using AI-based tools to increase efficiency, strengthen accountability, and ensure administrative transparency. In this context, anomaly detection, predictive analytics, and intelligent risk profiling systems have begun to be widely used in public administration and auditing processes (Anomah, 2025: 1). These opportunities offered by AI technologies enable the more effective use of public resources while also contributing to a more systematic, continuous, and risk-oriented structure of auditing processes. The integration of AI into public systems is of great importance for public administration to become more functional. As a result of this integration, it becomes possible to provide public services to citizens more quickly, accurately, and efficiently; this contributes to the smooth running of transactions and thus to the increase in social welfare (Bilgiç, 2026: 150). In this context, AI integration is no longer considered merely a long-term goal for public institutions, but a necessary requirement to maintain their institutional validity and effectiveness in the digital age. However, the successful implementation of artificial intelligence in public administration and auditing represents a multi-dimensional process that cannot be explained solely by technical infrastructure investments. Successful AI adoption requires a holistic approach that includes not only a technological upgrade but also institutional readiness and human resource transformation (Anomah, 2025: 1). Public employees' attitudes towards technology, their willingness to use new systems, and their perceptions of these technologies directly affect the AI adoption applications at the institutional level. Therefore, explaining why and under what conditions AI is adopted in public institutions is of critical importance both for the digital transformation literature and for public administration and auditing practices.

Despite growing interest in the use of artificial intelligence, whilst existing studies largely focus on technological capabilities and performance outcomes, the role of technological readiness in shaping the use of artificial intelligence through cognitive mechanisms—particularly in the context of public administration and auditing—has been relatively under-researched. Furthermore, the sequential mediating roles of perceived ease of use and perceived usefulness in this relationship have also received limited attention. The research's aim is to explore the serial multiple mediation effect of perceived ease of use and perceived usefulness of technology readiness in the AI adoption in public administration and auditing. More specifically, this study aims to uncover the mechanism by which technological readiness, as measured through perceived ease of use and perceived usefulness in the public sector context, influences the adoption of artificial intelligence.

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This study aims to fill a significant gap in the literature by focusing on the human and organizational factors that determine the success of digital transformation in the field of public administration and auditing. In this way, the study contributes to the literature by integrating technological readiness into AI adoption models and empirically examining the cognitive mechanisms underlying this relationship through a serial mediation framework. The adoption of AI applications in public institutions is closely related to the level of technological readiness of managers and auditors, beyond technical infrastructure and legal regulations. In this context, revealing how technological readiness shapes the AI adoption through cognitive evaluations such as perceived ease of use and perceived usefulness is critically important for the design of digital transformation policies in public administration. The research findings are expected to contribute to the more effective, sustainable, and acceptable implementation of AI-based applications in public institutions. At the same time, these findings are intended to guide policies and practices aimed at strengthening fundamental principles such as efficiency, accountability, and risk-oriented approach in public auditing. From a practical perspective, the findings are expected to assist policymakers and practitioners in developing more effective digital transformation strategies by highlighting the role of human and cognitive factors, as well as the technological infrastructure. In this respect, the study provides an analytical framework that explains not only the "applicability" of technological innovations in public administration and auditing, but also how these innovations are adopted at the institutional level and through which mechanisms they are internalized.

2. Literature Review and Hypothesis Development

AI adoption in Public Administration and Auditing

Digital transformation is a multi-dimensional process that reshapes governance tools such as effectiveness, efficiency, and accountability in public administration and auditing. This transformation is characterized by the development of information and communication technologies and the integration of advanced technologies such as AI into managerial processes. Digitalization is not just a technical improvement, but a restructuring in the delivery of public services. Digital tools and platforms create a simplification effect in bureaucracy, adding features such as speed, accuracy, and accessibility to service delivery. In this context, it can be said that the interaction between public administration and technology is increasing and processes are adapting to management practices (Kaya, 2024: 128). Technological innovations have significant effects in public services, especially in increasing efficiency and effectiveness, citizen-based services, transparency, and accountability processes. Digitalization enables the automation of routine administrative processes, thus optimizing resource utilization. Thanks to the widespread use of information technologies, bureaucratic processes are accelerated, and service delivery costs are reduced (Boyalı, 2025: 211). However, e-government and digital platforms facilitate citizens' access to public services, leading to increased satisfaction levels. AI-based systems both provide personalized service delivery and contribute to rapid feedback on requests (Fibriyanita, 2024: 74). Furthermore, transactions conducted through digital channels increase the traceability of processes, reinforcing transparency and openness in public administration (Kaya, 2024: 130).

AI stands out as a unique and critical component of the digital transformation process. In public administration, AI, combined with technologies such as big data analytics and automation, transforms decision-making and control processes and service delivery mechanisms. AI systems provide the opportunity to extract meaning from complex data sets and generate predictions, leading to increased performance in public institutions. This integration is particularly important in the development of public policies and the effective and efficient use of public resources. The literature contains findings on the impact of AI applications on public administration and control. Firstly, it is stated that artificial intelligence applications provide efficiency and process optimization in public services. Automation enables public institutions to perform recurring administrative tasks at a lower cost and in a shorter time (Hardianto et al., 2025: 52-54).

It is also emphasized that AI is an application that improves the quality of public service delivery and citizen satisfaction. Chatbots, virtual assistants, and automated application processing systems facilitate citizens' communication with public institutions; they improve the service experience through 24/7 service delivery and personalized responses. This contributes to strengthening the understanding of "citizen-centricity" in public administration through digital mechanisms (Wirtz et al., 2019: 600). AI applications are also transforming public policy-making and decision-making processes. AI-supported decision support systems can predict the possible consequences of public policy options through data obtained from large and complex datasets, providing managers with evidence-based decision-making opportunities. This accelerates the transition from an intuitive decision-making approach to an analytical and data-driven governance model. The literature also highlights the significant impact of AI on transparency and oversight capacity in public administration. Thanks to technology-integrated audit systems, irregularities can be detected and public expenditures can be monitored (Vrabie, 2025: 4). Auditors can identify unusual transactions or risk indicators more quickly and accurately in this process (Sawiz, 2024). Automated data analysis, ongoing monitoring, and strategic resource management enable auditors to devote their attention to high-risk and judgment-intensive tasks (Anomah, 2025: 1). AI can contribute to increased efficiency, especially in areas such as financial auditing and internal control assessment. Therefore, it is possible to say that AI plays an important role in determining audit strategies in the public sector.

It is also emphasized that AI applications have a transformative role on institutional structures and public employees. AI taking over routine tasks performed by public employees directs employees towards more strategic and analytical roles. This situation highlights a competency-based transformation in public institutions (Ağdeniz, 2024: 115). Thanks to the capacity of AI-based systems to automate routine and repetitive audit tasks, internal auditors can allocate their time and resources to more effective activities (Özyiğit, 2023: 30). This manifests itself in increased performance, quality, and efficiency.

The adoption of AI applications in public administration and auditing is a multi-dimensional process that cannot be limited solely to technological infrastructure or institutional arrangements. Individuals' tendencies, perceptions, and evaluations towards technology play a significant role in this process.

Technological Readiness

Technological readiness refers to the general tendencies of individuals to adopt and use new technologies, including psychological elements and inhibitory factors used to predict an individual's inclination to adopt a new technology (Abdo-Salloum and Al-Mousawi, 2025: 3). It shapes attitudes towards technological innovations through dimensions such as optimism, innovativeness, discomfort, and distrust (Parasuraman, 2000). The adoption of AI technology affects many sectors globally (Demir et al., 2024: 189). Public administration is one of them. The level of technological readiness of employees working in the field of public administration and auditing directly affects how complex and transformative technologies such as AI are perceived. Technological readiness refers to a person's aptitude for effectively using new technologies in professional or non-professional environments (Khalil et al., 2026: 5). Technological readiness can be described not merely as preparation for the AI adoption, but as a continuous condition necessary to achieve true AI maturity (Alam et al., 2025: 10). Generally, AI, which collects and analyzes data for decision-making processes in information technology, is considered more intelligent than information systems and transforms them into intelligent systems, enabling greater automation and optimization of information systems (Damerji and Salimi, 2021: 107).

Accordingly, it is assumed that technological readiness has a direct impact on the AI adoption. Many studies in the literature examine the impact of technological readiness on the AI adoption (Damerji and Salimi, 2021; Demir et al., 2024; Alam et al., 2025; Abdo-Salloum and Al-Mousawi, 2025). In line with these theoretical approaches, the following hypotheses are proposed:

H1: Technology readiness has an impact on the AI adoption.

Technology Acceptance Model

Many different models have been presented in the literature to investigate individuals' intentions regarding the acceptance and adoption of technology. One of these is the Technology Acceptance Model (TAM), first proposed in a study by Davis (1985) and subsequently developed by Davis, Bagozzi, and Warshaw (1989). This model focuses on attitudinal explanations of individuals' intentions to use a technology or service. This model is rooted in comprehensive theoretical frameworks such as rational action theory and planned behavior theory (Horst et al., 2007: 1839). Due to its ease of adaptability, validity, and accuracy, TAM has become one of the most widely used models for measuring technology acceptance (Çelik and Orhan, 2021: 214).

The TAM suggests that individuals' emerging usage behaviors are determined by behavioral intention, which reflects their usage attitude. Attitudes towards use are constructed through perceived usefulness and perceived ease of use (Horst et al., 2007: 1839), and these two concepts are considered key factors in the integration of new technologies (Abdo-Salloum and Al-Mousawi, 2025: 3). Today, the active use of information technologies is essential for increasing the effectiveness and efficiency of public services (Hawari et al., 2025: 49). Therefore, the TAM has been used in many studies in the field of public administration (Wang, 2002; Horst et al., 2007, Yeke et al., 2019). It is predicted that technological readiness is also a determining factor in the perceived ease of use of AI applications. It can be said that individuals who are more technologically adept perceive less cognitive effort in learning and using new systems; therefore, they evaluate these systems as more user-friendly. Similarly, the level of technological readiness is expected to influence perceived usefulness. It is stated that individuals open to technological innovations more easily recognize the potential contributions of AI applications to job performance, productivity, and control quality, and evaluate these technologies as more beneficial (Collantes, 2007: 273). In line with these theoretical approaches, the following hypotheses are proposed:

H2: Technology readiness influences perceived ease of use.
H3: Technology readiness influences perceived usefulness.

The use of information and communication technologies in public administration provides usefulness in terms of democratic administration, economic administration, and solution-oriented and proactive administration (Saylam, 2021: 277). According to the TAM, the perception that a system is easy to use strengthens the perception that the system is useful (Davis, 1989). In the context of public administration and auditing, given the complex and technical nature of AI applications, the perception of ease of use is expected to shape usefulness evaluations. In line with these theoretical approaches, the following hypotheses are proposed:

H4: Perceived ease of use influences perceived usefulness.

The usefulness provided by AI technologies have become increasingly attractive to public institutions (Saylam, 2021: 272). The assumption that perceived ease of use has a direct influence on the AI adoption is also one of the fundamental elements of the model. Systems perceived as difficult to use and having high learning costs are less likely to be adopted by public employees; Conversely, the adoption of systems perceived as user-friendly accelerates (Davis et al., 1989).

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When users perceive an application as easy to use, they are more motivated to continue using it (Hawari et al., 2025: 53).

Finally, perceived usefulness is considered a crucial factor in explaining the AI adoption. For a technology to be adopted in the field of public administration and auditing, it is expected to offer tangible contributions such as increasing auditing effectiveness, reducing errors and risks, and improving decision-making processes (Venkatesh et al., 2003: 446). In line with these theoretical approaches, the following hypotheses are proposed:

H5: Perceived ease of use influences the AI adoption.
H6: Perceived usefulness influences the AI adoption.

In the context of AI technologies, based on evidence in the literature indicating a relationship between technology readiness and technology adoption (Damerji and Salimi, 2021: 112; Anh et al., 2024: 7), it is hypothesized that perceived ease of use, as well as perceived usefulness, will mediate the effect of technology readiness on AI adoption. In line with these theoretical approaches, the following hypotheses are proposed:

H7: Perceived ease of use mediates the effect of technology readiness on the AI adoption.
H8: Perceived usefulness mediates the effect of technology readiness on the AI adoption.
H9: Perceived ease of use and perceived usefulness have a serial mediating effect on the effect of technology readiness on the AI adoption.

In line with the theoretical approaches presented above, the research model, which reveals the relationships between the variables of technology readiness, perceived ease of use, perceived usefulness, and AI adoption, as well as the hypotheses developed within the scope of the research, in a holistic structure, is presented in Figure 1.

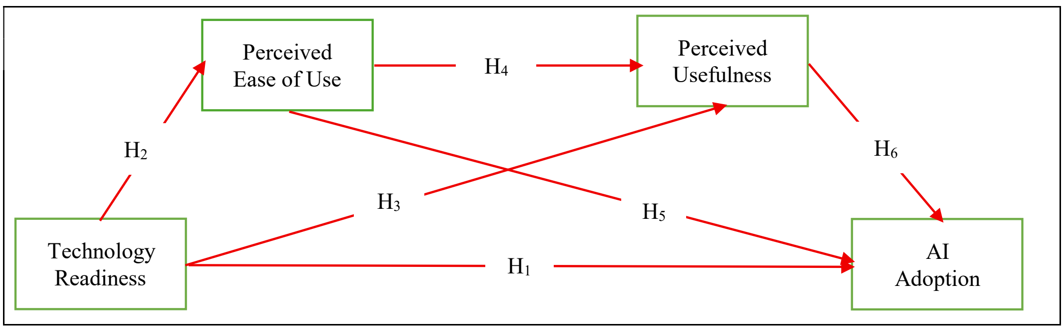

Figure 1. Research model

3. Methodology

Data collection and research sample

This research was conducted within the framework of a cross-sectional research design, collecting data over a specific time period. The main population of the research consists of public employees throughout Türkiye. In the sampling process, it was decided to use both convenience and snowball sampling methods, which are non-random sampling methods. The main reason for choosing these methods is that reaching the main population is not feasible in terms of both time and cost. According to the website of the Presidency of the Republic of Türkiye's Ministry of Strategy and Budget, there are a total of 5,375,724 public employees in Türkiye as of September 2025 (www.sbb.gov.tr, 2026). Based on a 95% confidence level and a 5% margin of error, it was determined that the minimum sample size that can represent the main population should be 384 people (Yazıcıoğlu and Erdoğan, 2004: 50). After obtaining ethical approval from the Sakarya University of Applied Sciences Rectorate Ethics Committee on May 7, 2025, with approval number E-26428519-050.99-172618, researchers requested that public employees, easily accessible via email and social media platforms (WhatsApp, Instagram, and Facebook), complete an electronically prepared survey form on "Google Forms" and forward it to at least one other public employee. Thus, data was collected from 409 public employees who voluntarily agreed to participate in the research.

It was determined that 54.3% of the public employees included in the sample were women. According to the analysis results, 48.9% of the public employees were civil servants; the highest percentage in the age variable was 39.6% in the 42 years and older group, and in terms of education level, it was highest among bachelor's degree graduates at 49.6%. The demographic data obtained by applying frequency and percentage analysis within the scope of the research are presented in Table 1 below.

Table 1. Sociodemographic Profile of the Sample

Characteristics	Description	N	%	Characteristics	Description	N	%
Gender	**Male**	187	%45.7	**Position**	**Manager**	72	%17.6
					Staff	200	%48.9
	Female	222	%54.3		**Other**	137	%33.5
Age	**18–25 years old**	31	%7.6	**Education**	**High School**	28	%6.8
	26–33 years old	79	%19.3		**Associate Degree**	43	%9.8
	33–41 years old	134	%33.5		**Bachelor's Degree**	200	%49.6
	>42 years old	165	%39.6		**Graduate Degree**	138	%33.7
Experiences	**<5 years**	75	%18.3	**Organizational Tenure**	**<5 years**	127	%31.1
	5–10 years	80	%19.6		**5–10 years**	106	%25.9
	10–15 years	89	%21.8		**10–15 years**	85	%20.8
	>20 years	165	%40.3		**>20 years**	91	%22.2

Source: Authors' calculations

Measurement

Data were obtained using the survey method, which is commonly used in social sciences for collecting primary data. The survey form, prepared electronically on “Google Forms”, consists of two sections and 38 items. The first section contains 7 items to determine demographic characteristics, and the second section contains 31 items to measure the levels of technology readiness, AI adoption, perceived usefulness, and ease of use among public employees. During the application of the measurement tools, it was evaluated using a 5-point Likert scale, where 1=strongly disagree; 5=strongly agree.

Technology Readiness Scale: To measure the technology readiness levels of public employees, the “Technology Readiness Scale” developed by Parasuraman and Colby (2015) was used. This 16-item measurement tool has four dimensions: optimism, innovativeness, discomfort, and insecurity. Parasuraman and Colby (2015: 67) reported that the Cronbach α coefficients of the four-item dimensions of the scale ranged from 0.68 to 0.90. Technology Acceptance Scale: To determine public employees’ perceptions of ease of use and usefulness regarding technology use, Davis’s (1989).

Technology Acceptance Model (TAM) framework’s “Technology Acceptance Scale” was used. This scale consists of two dimensions: the first 6 items are “perceived usefulness” and the other 6 items are “perceived ease of use”. Davis (1989: 319) reported the Cronbach α coefficient as 0.94 for perceived ease of use and 0.98 for perceived usefulness.

AI Adoption Scale: To measure the level of artificial intelligence adoption among public employees, the “Artificial Intelligence Adoption Scale” developed by Handoko (2021) was used. The Cronbach α coefficient of this 3-item, one-dimensional measurement tool was reported as 0.868 by Handoko (2021: 5977).

Analysis Procedures

In the present study, the dataset was examined for missing values, outliers, and normal distribution before starting the analysis. The study found no missing or missing data in the dataset. Cook’s distance values were examined to identify multivariate outliers in the dataset. The highest calculated Cook’s distance value of 0.0794 (Cook’s distance value <1) indicated the absence of outliers that disrupted the multivariate normal distribution in the dataset (Field, 2009). Skewness and kurtosis coefficients were examined to test whether the dataset met the normal distribution criteria. Calculated skewness and kurtosis values within the ±1 range indicate that the dataset satisfies the normal distribution criteria. The analyses revealed that the skewness and kurtosis values were within the ±1 range (Technology Readiness = [.767, .857], Perceived Ease of Use = [-.597, .441], Perceived Usefulness = [-.499, .372], and AI Adoption = [-.679, .009]). Therefore, the dataset was assumed to exhibit a normal distribution (Tabachnick and Fidell, 2015).

To examine the scales' factor structures and verify their measurement validity, a Confirmatory Factor Analysis (CFA) was conducted. As part of the reliability studies, Cronbach's Alpha reliability coefficients were examined. Pearson correlation coefficients were calculated to determine the direction and level of the relationship between the variables. The role of perceived usefulness and ease of use variables as serial mediators in the relationship between technology readiness and AI adoption was examined through Model 6 – Serial Mediator Variable Analysis in the PROCESS Macro extension running on SPSS. IBM SPSS 25.0 and IBM AMOS 24.0, as well as Andrew F. Hayes' (2018) PROCESS v4.2 macro application running on SPSS, were used for all statistical analyses.

4. Findings

Reliability and Validity

Before examining the research hypotheses, CFA was conducted to verify the factor structures and ensure the measurement validity of the instruments used. Accordingly, a first-level CFA was performed to validate the four-factor structure of the technology readiness scale (optimism, innovativeness, discomfort, and insecurity), the two-factor structure of the technology acceptance scale (perceived usefulness and perceived ease of use), and the single-factor structure of the AI adoption scale. Subsequently, a second-level CFA was performed for the technology readiness scale as a whole. The fit values obtained for the measurement models of the scales are presented below.

Table 2. CFA Model Fit Indices

Variables		**$\Delta\chi^2$**	**df**	**$\Delta\chi^2$/ df $\leq$4-5**	**RMSEA $\leq$.08**	**AGFI $\geq$.90**	**GFI $\geq$.90**	**CFI $\geq$.90**	**NFI $\geq$.90**
Technology Readiness	First-level	230.621	96	2.402	.059	.907	.934	.913	.947
Technology Readiness	Second-level	219.125	95	2.307	.057	.911	.938	.917	.951
Technology Acceptance Scale	First-level	163.756	49	3.342	.076	.903	.939	.975	.965
AI Adoption	First-level	76.464	24	3.186	.073	.922	.958	.976	.983

Source: Authors' calculations

The DFA results reported in Table 2 include the first-level structure of the technology readiness scale, comprising four factors: optimism, innovation, discomfort, and insecurity; the second-level structure where these dimensions are grouped under the overarching factor of technology readiness; and also the first-level structures of the technology acceptance and AI adoption scales. DFA results show that the technology readiness scale has both first

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level [$\chi^2(96) = 230.621$, $p < .001$, $\chi^2/df = 2.402$, RMSEA = .059, AGFI = .907, GFI = .934, CFI = .913, NFI = .947] and second level [$\chi^2(95) = 219.125$, $p < .001$, $\chi^2/df = 2.307$, RMSEA = .057, AGFI = .911, GFI = .938, CFI = .917, NFI = .951], and the technology acceptance scale has first level [$\chi^2(49) = 163.756$, $p < .001$, $\chi^2/df = 3.342$, RMSEA = .076, AGFI = .903, GFI = .939, CFI = .975, NFI = .965]. The goodness-of-fit indices for the first-level structure of the AI adoption scale [$\chi^2(24) = 76.464$, $p < .001$, $\chi^2/df = 3.186$, RMSEA = .073, AGFI = .922, GFI = .958, CFI = .976, NFI = .983] are within the acceptable limits suggested in the SEM literature. These results show that the data fit the proposed model well and support the validity of the factor structures of the four measurement models (Hair et al., 2014; Gürbüz, 2024).

Table 3. Correlation Coefficients

Variables	Mean	S	1	2	3	4
1.Technology Readiness	3.44	.482	(.778)			
2.Perceived Ease of Use	3.87	.741	.417**	(.942)		
3.Perceived Usefulness	3.75	.731	.501**	.821**	(.925)	
4. AI Adoption	3.74	.961	.461**	.678**	.715**	(.928)

Source: Authors' calculations

As shown in Table 3, the mean score of the technology readiness scale (M = 3.44, S = .482) is lower than the mean scores of the perceived ease of use scale (M = 3.87, S = .741), the perceived usefulness scale (M = 3.75, S = .731), and the AI adoption scale (M = 3.74, S = .961). The results of the Pearson correlation analysis indicated that technology readiness was positively correlated with perceived ease of use ($r = .417$, $p < .01$), perceived usefulness ($r = .501$, $p < .01$), and AI adoption ($r = .461$, $p < .01$). Perceived ease of use was positively correlated with perceived usefulness ($r = .821$, $p < .01$) and AI adoption ($r = .678$, $p < .01$), while perceived usefulness was also positively correlated with AI adoption ($r = .715$, $p < .01$). In addition, the Cronbach's alpha coefficients, indicating the reliability of the scales, were found to be greater than .70.

Mediation Analysis and Hypothesis Testing

To reveal the serial mediation effect of perceived usefulness and perceived ease of use, respectively, in the relationship between technology readiness and AI adoption, the PROCESS Macro v4.2 application developed by Hayes (2018) was used. To test the serial multiple mediation effect in a single model using the Bootstrap method, Model 6 was chosen, where technology readiness (X) is defined as the independent variable, AI adoption (Y) as the dependent variable, and perceived ease of use (M1) and perceived usefulness (M2) as the mediating variables, respectively. For the analysis (mediation effect analysis), confidence intervals were calculated at a 95% confidence level with a 5,000 resampling option. In the literature, when evaluating analysis results using the Bootstrap technique, it is generally accepted that the indirect effect (mediation effect) is statistically significant if there is no zero value at the lower or upper limit of the confidence interval (Preacher & Hayes, 2004; Zhao et al., 2010).

Table 4. Bootstrap Mediation Analysis Results

Variables	Effects				BootCI		Model Summary		
	β	S	t	p	BootLLCI	BootULCI	R^2	Model F	Sig. F
(X) → (Y)	.461	.088	10.485	.000	.747	1.091	.213	109.934	.000
(X) → (M1)	.417	.069	9.261	.000	.505	.777	.174	85.774	.000
(X) → (M2)	.192	.045	6.467	.000	.203	.379	.705	484.215	.000
(M1) → (M2)	.741	.029	24.967	.000	.673	.789			
(X) → (Y)	.135	.077	3.518	.000	.119	.421	.550	165.179	.000
(M1) → (Y)	.279	.076	4.781	.000	.213	.511			
(M2) → (Y)	.418	.081	6.811	.000	.390	.707			

Source: Authors' calculations

As shown in Table 4, technology readiness had a positive and statistically significant effect on the AI adoption (β = .461, t = 10.485, p < .001, 95% CI [.747, 1.091]). 21.3% (R^2 = .213) of the variation in the AI adoption is explained by the technology readiness variable. Therefore, hypothesis H1 is accepted.

Technology readiness had a positive and statistically significant effect on perceived ease of use (β = .417, t = 9.261, p < .001, 95% CI [.505, .777]). 17.4% (R^2 = .174) of the variation in the perceived ease of use variable is explained by the technology readiness variable. Therefore, hypothesis H2 is accepted.

Technology readiness had a positive and statistically significant effect on perceived usefulness (β = .192, t = 6.467, p < .001, 95% CI [.203, .379]). In the third stage, it was determined that perceived ease of use had a positive and statistically significant effect on perceived usefulness (β = .741, t = 24.967, p < .001, 95% CI [.673, .789]). 70.5% of the variation in the perceived usefulness variable (R^2 = .705) is explained by the variables of technology readiness and perceived ease of use. Accordingly, hypotheses H3 and H4 are accepted.

With the sequential inclusion of mediating variables, technology readiness had a positive and statistically significant effect on AI adoption (β = .135, t = 3.518, p < .001, 95% CI [.119, .421]), perceived ease of use had a positive effect on AI adoption (β = .279, t = 4.781, p < .001, 95% CI [.213, .511]), and perceived usefulness had a positive effect on AI adoption (β = .418, t = 6.811, p < .001, 95% CI [.390, .707]). 55% of the variation in the AI adoption variable (R^2 = .550) is explained by the variables of technology readiness, perceived ease of use, and perceived usefulness. Accordingly, hypotheses H5 and H6 are accepted.

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Table 5. Bootstrapped Serial Mediation Results

Total, Direct, and Indirect Effects of X on Y	Effect	SE	t	Sig.	BootCI	
					BootLLCI	BootULCI
Total effect of X on Y	.919	.088	10.485	.000	.747	1.091
Direct effect of X on Y	.270	.077	3.518	.000	.119	.421
			BootCI			
Indirect effect(s) of X on Y	Effect	SE	BootLLCI	BootULCI	Mediation Type	
(X) → (Y)	.649	.069	.520	.792		
(X) → (M1) → (Y)	.232	.063	.117	.363	Partial Mediation	
(X) → (M2) → (Y)	.160	.039	.089	.244	Partial Mediation	
(X) → (M1) → (M2) → (Y)	.257	.048	.168	.356	Serial Mediation	

Source: Authors' calculations

Table 5 shows that the overall effect of technological readiness (X) on the adoption of artificial intelligence (Y) is significant ($\beta = .919$, $t = 10.485$, $p < .001$, 95%CI [.747 1.091]). A portion of this effect occurs directly ($\beta = .270$, $t = 3.518$, $p < .001$, 95%CI [.119 .421]), while another portion occurs indirectly ($\beta = .649$, 95%CI [.520, .792]). Furthermore, it was determined that technology readiness (X) has a significant effect on the AI adoption (Y) through perceived ease of use (M1) ($\beta = .232$, 95% CI [.0117, .363]), on the AI adoption (Y) through perceived usefulness (M2) ($\beta = .160$, 95% CI [.089; .244]), and on the AI adoption (Y) through perceived ease of use (M1) and perceived usefulness (M2) ($\beta = .257$, $p < .01$; 95% CI [.168; .356]). Accordingly, hypotheses H7, H8, and H9 were accepted.

5. Conclusions

This research examined the effect of public employees' level of technology readiness on the AI adoption within the framework of the Technology Acceptance Model and with a serial multiple mediation role. The findings are consistent with theoretical expectations and yield results that are consistent within the model. In summary, this study demonstrates that technological readiness plays a crucial role in the AI adoption in public administration and auditing, both directly and indirectly through cognitive mechanisms.

Firstly, it has been observed that technological readiness directly and significantly affects the AI adoption. Therefore, it can be said that public employees with high levels of optimism and innovation towards technology, but low levels of discomfort and distrust, are more inclined to adopt AI applications. This result is consistent with Alam et al. 2025, Hawari et al. 2025, and Abdo-Salloum and Al-Mousawi 2025. The analyses clearly show that the individual technology tendencies of public employees have not only attitudinal but also behavioral consequences. Technological readiness on the AI adoption draws attention to the human resource dimension of digital transformation in public institutions. In public administration and auditing, service delivery and internal control processes are increasingly based on data-driven systems, and the functionality of these systems progresses in direct proportion to the attitudes of public employees towards technology. Even the most advanced AI applications cannot be expected to perform as expected in an organizational structure where individuals are not technologically ready. Therefore, digitalization strategies in the public sector should be considered not only as infrastructure investments but also as a transformation of organizational culture.

However, the most striking aspect of the study is how it demonstrates this relationship. The research results demonstrate that technological readiness influences AI adoption not only directly but also indirectly through perceived ease of use and perceived usefulness. In particular, perceived ease of use strongly influences perceived usefulness; these two variables together form a series of multiple mediations. Therefore, it appears that public employees find a technology useful to a large extent dependent on how easily they can use it. This confirms that the technology adoption process operates through a cognitive evaluation chain. From a public audit perspective, the series of multiple mediations of perceived ease of use and perceived usefulness is particularly noteworthy. The more understandable and applicable a system is to public employees, the more useful and adoptable that system becomes. This highlights the importance of user-friendly interfaces and clear procedures in the design of AI-powered internal audit, performance monitoring, and risk analysis systems. From this perspective, complex, closed, and difficult-to-understand audit mechanisms in the public sector will not only reduce adoption rates but also weaken the goals of transparency and accountability. The findings suggest that AI applications should be positioned as decision support systems in public administration and auditing. As perceived usefulness increase, the adoption level rises significantly, indicating that digital transformation accelerates when public employees view technology as a tool to facilitate work processes. In this context, it is important that AI is presented as a mechanism that strengthens, rather than replaces, human judgment in auditing processes, so that public employees do not perceive AI as a threat.

Generally speaking, employees' attitudes towards technology, their perceptions of ease of use, and their evaluations of the usefulness they will derive from technology are fundamental elements of the technology adoption process. Therefore, it is important that training programs and application processes in the public sector are designed with a user experience-based approach. It is clear that investing solely in technical infrastructure is insufficient for the widespread adoption of AI applications in public institutions. Digitalization, from the perspective of public administration and auditing, is not merely a software update; it is a holistic management issue that transforms both human and organizational dimensions. In conclusion, this study contributes to the literature by addressing the relationship between technological readiness and AI adoption within a multidimensional framework; it also provides a human-centered perspective on digital transformation processes in public administration.

The results of this study contribute significantly to the literature from both theoretical and practical perspectives. Firstly, this study contributes to the Technology Acceptance Model literature by incorporating technology readiness as a predictor variable in the context of AI adoption. Secondly, it reveals the underlying cognitive mechanisms of this relationship through a serial multimediation model that includes perceived ease of use and perceived usefulness. Thirdly, it provides empirical evidence from the public sector, where such integrative approaches have been limited. From a practical perspective, the findings emphasize that digital transformation in public administration should not be limited to technological investments alone but must also focus on human and organizational factors. In particular, the development of user-friendly systems and the enhancement of public employees' technological skills could significantly increase the use of AI.

Despite its contributions, the study has certain limitations. The use of cross-sectional data restricts causal interpretations. Furthermore, the findings are based on self-reported data, which may lead to response bias. Moreover, the focus on public sector staff may limit the generalizability of the results to other contexts. Future research could examine the factors shaping the AI adoption process in greater depth. In this regard, the role of variables such as trust in AI, perceived risk and organizational support could be explored in detail. Furthermore, incorporating elements such as ethical concerns, transparency and accountability into the model could provide a more holistic understanding of AI adoption, particularly within the context of public administration and oversight. In addition, longitudinal studies could shed light on the dynamic nature of the process by revealing changes in technological readiness and AI adoption over time. Comparative studies across different sectors or countries, meanwhile, can more clearly highlight the contextual differences in adoption processes.

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