



INTERNATIONAL JOURNAL
OF LAW, GOVERNMENT
AND COMMUNICATION
(IJLGC)


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ENHANCING DIGITAL TRANSFORMATION IN THE UNITED ARAB EMIRATES: EXAMINING THE TECHNOLOGICAL, ORGANIZATIONAL, AND ENVIRONMENTAL DRIVERS SHAPING AI ADOPTION INTENTIONS AMONG GOVERNMENT EMPLOYEES

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Article Info:

Article history:

Received date: 20.04.2026

Revised date: 07.05.2026

Accepted date: 02.06.2026

Published date: 23.06.2026

To cite this document:

Al-Ameri, M. M. O., Zainuddin, M. T., Nawang, W. R. W. (2026). Enhancing Digital Transformation in The United Arab Emirates: Examining the Technological, Organizational, And Environmental Drivers Shaping AI Adoption Intentions

Abstract:

Artificial Intelligence (AI) has become a key driver of digital transformation in the United Arab Emirates (UAE), yet its adoption within government institutions remains uneven despite substantial national investments and policy support. This study investigates the technological, organizational, and environmental factors influencing government employees' intentions to adopt AI. Drawing upon the Technology Acceptance Model (TAM) and the Technology–Organization–Environment (TOE) framework, the study proposes an integrated model that examines the effects of System Quality, Service Quality, Information Quality, Technical Support, AI Awareness, Top Management Support, Government Policy, Industry Pressure, and Data Privacy Concerns on Perceived Usefulness, Perceived Ease of Use, Trust, and Intention to Adopt AI. User Readiness was also examined as a moderating variable. A quantitative research design was employed, and data were collected from 425 government employees across the seven emirates of the UAE. The data were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM). The findings reveal that technological quality factors, organizational support, and

Among Government Employees.
*International Journal of Law,
Government and
Communication*, 11(44), 240-
265.

environmental conditions significantly influence Perceived Usefulness and Perceived Ease of Use. Consistent with TAM, Perceived Ease of Use positively affects Perceived Usefulness, while both constructs significantly enhance Trust. Trust emerged as the strongest predictor of Intention to Adopt AI, highlighting its critical role in fostering AI acceptance among public-sector employees. In addition, User Readiness significantly strengthened the relationship between technology perceptions and adoption intention. The model demonstrated substantial explanatory power, accounting for 78.1% of the variance in Intention to Adopt AI. The study contributes to the AI adoption literature by integrating TAM and TOE within a public-sector context and highlighting the importance of trust and user readiness in technology acceptance. The findings provide practical insights for policymakers and government leaders seeking to accelerate AI-driven digital transformation through improved technological infrastructure, organizational preparedness, employee awareness, and trust-building initiatives.

DOI: 10.35631/IJLGC.1144015 **Keyword:**

Artificial Intelligence (AI) Adoption, Government Employee, UAE, Consumers, Technology Acceptance Model (TAM), Technology-Organization-Environment (TOE).



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Introduction

Artificial Intelligence (AI) is a disruptive technology that is rapidly transforming the modern landscape and redefining the interaction between humans and machines and ushering in a new era of digital governance. Although there are many definitions in existence, AI in broad sense may be viewed as systems that can sense the environment, process complex data as well as perform autonomous decision-making to achieve certain goals (Spring et al. 2022). The AI market is also growing exponentially in the United Arab Emirates (UAE), with a Compound Annual Growth Rate (CAGR) of 43.9 percent through 2030 and an estimated market size of USD 3.47 billion in 2023 (Al Tawhidi & Bourini, 2024). The COVID-19 pandemic further accelerated this trend, requiring a boom in the number of AI-based digital services. Although this is the current macroeconomic development, the penetration of AI is still very skewed among industries. Although about 66 percent of UAE consumers state that they use AI in the retail and consumer goods industry, other vital sectors are lagging, which is a significant missed opportunity to create value (Hamzah, 2025). In the context of the public sector, perceived usefulness, perceived ease of use, and underlying trust are all critical factors to user acceptance (Mishra et al. 2024). Obstacles to systemic adoption often include skills gaps, privacy concerns, technical complexity, and simply the lack of transparency and trust in AI algorithms, players that undermine transparency and trust (Mehrotra et al. 2024; Tasnim et al. 2025). Interestingly,

the existing literature shows that there are critical gaps in terms of the dynamics of AI adoption among UAE government servants, in particular, the mediating roles of perceived risk and trust. To fill this gap, the current study is a synthesis of the Technology Acceptance Model (TAM) and the Technology-Organization-Environment (TOE) model. It systematically analyzes the influences of technological, organizational and environmental conditions on the sense of usefulness and ease of use. Further, it takes trust as a mediating and user preparedness as the moderating variable of AI adoption intention. The study has a theoretical contribution to the body of knowledge, which is that it fills gaps in the literature to bridge TAM and TOE within the unique socio-technical context of the UAE and ultimately equips policymakers, organizational leaders, and developers with the knowledge needed to mitigate risks, ensure that AI strategies align with cultural values, and drive sustainable development (Saragih et al. 2025).

Problem Statement

Although it is widely accepted that AI is a potent force that promotes productivity in the current global economy, structural assimilation of AI in organizational context is highly inconsistent (Horani et al. 2025). At the global scale, research shows that although 45 percent of organizations are already piloting AI initiatives, almost 36 percent of organizations, however, still lack a coherent AI strategy (Radwan et al. 2026). Even in the peculiar situation of the UAE, a country on the frontline of the technological revolution and a rapidly growing AI market, a huge gap still exists between the strategic intent and smooth operational execution. The root of the matter is the multifaceted nature of the challenges in the way of complete AI adoption among government servants (Dwivedi et al. 2021). Although the UAE has been rapidly shifting to a digitalized economy, systemic inefficiencies, a lack of operational transparency, and human error are still contributing to the inability to fully optimize the public sector (Alshehhi et al. 2024). To add to this is the black box phenomenon of algorithms, which deprives systems of their interpretability and leaves the end-users with little understanding of how critical decisions are made. Such lack of transparency, coupled with deep-seated fears about data privacy, displacement of the workforce, and ethical liabilities, breeds an overall lack of trust that halts meaningful integration of technology (Ryan & Harrison, 2000; Aboelazm, 2025; Gkikas & Gkikas, 2026). Thus, the importance of growing integration of AI technologies within the UAE's digital economy, with emphasis on the public sector as the user as well as acting as policy manager, would create opportunities for advancing Islamic marketing practices, particularly through enhanced customer insights, personalized service experiences, and more efficient delivery of Shariah-compliant products and services (Zainuddin, 2016).

Literature Review

Artificial Intelligence Adoption in the Government Sector

Artificial Intelligence (AI) refers to systems capable of performing tasks that typically require human intelligence, including learning, reasoning, problem-solving, and decision-making (Archana, 2025). In the public sector, AI has emerged as an important tool for enhancing operational efficiency, service delivery, and policy implementation. AI applications enable government agencies to automate routine tasks, improve decision-making processes, and reduce operational errors. As governments increasingly pursue digital transformation initiatives, AI adoption has become a strategic priority for improving public-sector performance and citizen services (Al Ali & Khalil, 2025; Elliott, 2019).

Theoretical Foundations: Integration of TAM and TOE

This study integrates the Technology Acceptance Model (TAM) and the Technology-Organization-Environment (TOE) framework to explain AI adoption among government employees. TAM posits that technology acceptance is primarily determined by Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) (Davis, 1989; Venkatesh & Davis, 2000). Perceived Usefulness refers to the extent to which technology enhances job performance, whereas Perceived Ease of Use reflects the degree to which the technology is perceived as effortless to use. While TAM focuses on individual perceptions, the TOE framework extends the analysis by incorporating organizational and environmental influences on technology adoption (Drazin, 1991). The technological context includes factors such as System Quality, Service Quality, and Information Quality. The organizational context encompasses Technical Support, AI Awareness, and Top Management Support, whereas the environmental context includes Government Policy, Industry Pressure, and Data Privacy Concerns. The integration of TAM and TOE provides a comprehensive framework for understanding both individual and contextual factors influencing AI adoption.

Technological Factors

Technological quality is a critical determinant of technology acceptance (Khalil & Al-Ali, 2026). System Quality reflects the reliability, usability, and efficiency of AI systems, while Information Quality refers to the accuracy, relevance, and timeliness of information generated by the system (Fu et al. 2024). Service Quality captures the responsiveness and effectiveness of support services available to users (Abd Aziz et al. 2024; Satyro et al. 2024). High-quality technological infrastructure reduces complexity, enhances user experience, and increases perceptions of usefulness and ease of use. Consequently, employees are more likely to accept AI technologies when systems are reliable, informative, and supported by effective service mechanisms.

Organizational Factors

Organizational readiness plays a significant role in facilitating AI adoption. Top Management Support reflects leadership commitment, resource allocation, and strategic guidance toward technology implementation (Oyetade et al. 2024). Strong managerial support helps reduce resistance to change and promotes a culture of innovation (Rogers, 2003). Similarly, AI Awareness represents employees' understanding of AI technologies and their potential organizational benefits (Felemban et al. 2024). Employees who possess greater awareness and knowledge of AI are generally more confident in using such technologies and are more likely to perceive them as useful and easy to use (Flavián et al. 2022). Technical Support further contributes to successful implementation by providing training, troubleshooting assistance, and ongoing guidance. Effective technical support reduces uncertainty, enhances user confidence, and facilitates smoother technology adoption processes (Arpaci et al. 2012; Hong & Cho, 2023; Li & Xie, 2025).

Environmental Factors

The external environment also influences organizational technology adoption. Government Policy provides regulatory guidance, promotes responsible innovation, and establishes frameworks that encourage AI implementation. Supportive policies enhance confidence among

users and organizations by addressing concerns related to governance, accountability, and ethical AI deployment (Feldstein, 2021; Rane et al. 2024). Industry Pressure represents external expectations arising from technological competition and stakeholder demands. Organizations often adopt emerging technologies to maintain competitiveness, improve efficiency, and meet evolving service expectations (Bin-Nashwan et al. 2025). Together, government support and environmental pressures create favourable conditions for AI adoption.

Trust, Data Privacy Concerns, and User Readiness

Trust is widely recognized as a critical determinant of AI acceptance. It reflects users' confidence in the reliability, transparency, and ethical operation of AI systems (Lin et al. 2025). Trust becomes particularly important in public-sector settings where AI-assisted decisions may directly affect citizens and organizational outcomes. Data Privacy Concerns influence users' perceptions of risk associated with the collection, storage, and use of personal information. Concerns regarding privacy and security may reduce trust and hinder technology adoption if not adequately addressed (Custers et al. 2019). In addition, User Readiness reflects employees' psychological preparedness, digital competence, and willingness to embrace technological change (Benson, 2019). Individuals with higher levels of readiness are more likely to adapt to AI-enabled work environments and translate positive perceptions into actual adoption intentions (Arunachalam, H. (2025).

Theoretical Framework

Two of the most popular models are brought together by the theoretical framework of this study, which seeks to give a wholesome perspective of AI adoption, the Technology Acceptance Model (TAM) and the Technology-Organization-Environment (TOE) model. Whereas the TAM considers personal cognitive reactions to technology, the TOE framework takes into consideration the wider organizational and contextual influences that promote or impede innovation. The research framework of this study is shown in Figure 1.

Technology Acceptance Model (TAM) TAM, which was proposed by Davis (1989), is a theory of information systems that is used to explore the process through which users adopt and use new technologies. It is based on the premise that there are two major mental constructs that define whether a user is going to adopt a system. Firstly, the Perceived Usefulness (PU). This is the level to which a government servant thinks that using AI will lead to better job performance or a positive result. Secondly, the Perceived Ease of Use (PEOU), the degree to which a person is convinced that the work with AI technology will be free and simple to use. TAM can be utilized in this study to explain how the perceived utility and ease of AI tools have the direct impact on structuring the attitudes of the UAE government employees.

Technology-Organization-Environment (TOE) Framework TOE framework by Tornatzky & Fleischer (1990) investigates the process of innovation adoption by three different settings: Technological Context: Concentrates on internal and external technologies of the firm, namely System Quality, Service Quality and Information Quality. Organizational Context: It is the internal aspect, including Technical Support, Top Management Support, and AI Awareness. Environmental Context: External Pressures like Government Policy, Industry Pressure, and Data Privacy Concerns.

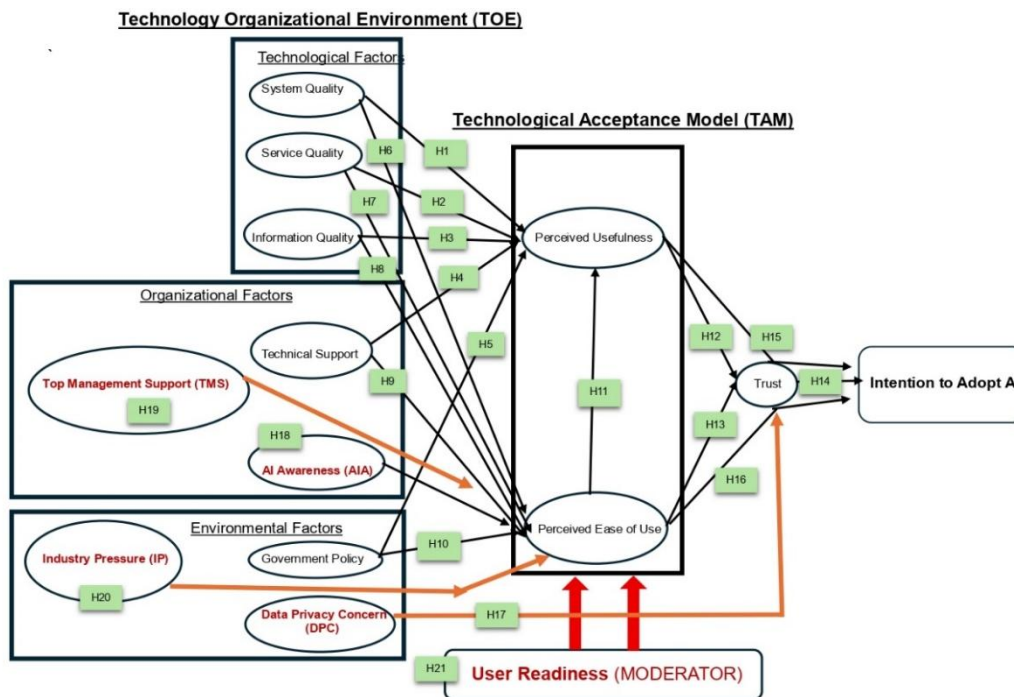


Figure 1: The Research Framework

Source: This study.

Research Methodology

Population and Sampling

It targeted employees of the UAE government who have either been exposed to or learned about AI in employment. They include the seven emirates, that is, Abi Dhabi, Dubai, Sharjah, Ajman, Umm Al-Quwain, Ras Al Khaimah and Fujairah, which also presupposes an extensive coverage of the region. A 95% confidence level at a margin of error of 5% was used to obtain a sample of 425 respondents. To address the problem of heterogeneity of the population, a stratified sampling method was employed whereby the respondents were stratified based on the emirate and a random sample was selected among the subgroups to reduce the biases and provide a true representation.

Instrument Development

The research instrument was developed based on an extensive review of the literature on Artificial Intelligence (AI) adoption, technology acceptance, digital transformation, and public-sector innovation. The questionnaire was designed to operationalize the constructions embedded within the integrated Technology-Organization-Environment (TOE) and Technology Acceptance Model (TAM) framework. All measurement items were adapted from previously validated studies to ensure content validity and contextual relevance to the UAE public sector.

The questionnaire consisted of three sections. The first section collected respondents' demographic information. The second section measured the TOE-related constructs, namely System Quality, Service Quality, Information Quality, Technical Support, Top Management Support, AI Awareness, Government Policy, Industry Pressure, and Data Privacy Concerns. The third section measured the TAM and behavioural constructs, including Perceived Ease of Use, Perceived Usefulness, Perceived Trust, User Readiness, and Intention to Adopt AI.

The measurement items were adapted from established studies in the information systems and technology adoption literature. The technological quality dimensions were adapted from prior Information Systems Success Model research, while the organizational, environmental, trust, and readiness constructs were adopted from previous studies examining technology adoption, organizational readiness, and AI implementation. Perceived Usefulness and Perceived Ease of Use were adapted from the original Technology Acceptance Model developed by Davis (1989) and its subsequent extensions. All items were measured using a five-point Likert scale ranging from 1 ("Strongly Disagree") to 5 ("Strongly Agree"). Prior to the main survey, the questionnaire was reviewed by academic experts and practitioners involved in AI implementation to establish content validity. A pilot study involving 50 government employees was subsequently conducted, and the results confirmed satisfactory reliability for all constructs. The final questionnaire was distributed electronically to government employees across the seven emirates of the UAE using a secure web-based survey platform. This approach facilitated efficient data collection and ensured broad geographical coverage. The adequacy of the measurement instrument was later confirmed through the PLS-SEM assessment, where all constructs demonstrated satisfactory reliability and validity, meeting the recommended thresholds for indicator loadings, internal consistency reliability, convergent validity, and discriminant validity.

Data Analysis: PLS-SEM

The data obtained is processed by the application of Partial Least Squares Structural Equation Modelling (PLS-SEM) via Smart-PLS software version 4, which is a method that presupposes a systematic estimation of the measurement and structural model. To check the measurement model, initially, it is checked that factor loading is more than 0.7 and the Average Variance Extracted (AVE) is over 0.5 and then the discriminant validity is checked through the Heterotrait-Monotrait (HTMT) criteria. The structural model is then used to test the hypotheses that were proposed using bootstrapping analysis to establish the significance of path coefficients using t-values and p-values. Lastly, the predictive ability of the model is assessed through the Coefficient of Determination (R^2), with a value above 0.25 indicating that the independent variables have a significant influence on the intention to adopt AI technology.

Findings: The Results of PLS Regression Analysis

Proportion of Variance Explained

The explanatory power of the proposed integrated Technology Acceptance Model (TAM) and Technology-Organization-Environment (TOE) framework was evaluated using the coefficient of determination (R^2). The results indicate that the model possesses substantial predictive capability in explaining the key endogenous constructs associated with AI adoption among government employees in the United Arab Emirates. The findings reveal that the model explains 68.4% of the variance in Perceived Ease of Use ($R^2 = 0.684$), suggesting that the

technological, organizational, and environmental factors incorporated in the study collectively exert a strong influence on employees' perceptions regarding the ease of interacting with AI-enabled systems. This substantial level of explained variance demonstrates the importance of system quality, service quality, information quality, technical support, government policy, AI awareness, top management support, and industry pressure in shaping users' perceptions of AI usability.

Similarly, the model accounts for 74.2% of the variance in Perceived Usefulness ($R^2 = 0.742$), indicating that the selected antecedent variables are highly effective in explaining how government servants evaluate the performance-enhancing benefits of AI technologies. This result confirms that both technological quality dimensions and user perceptions of ease of use play a critical role in strengthening beliefs regarding the usefulness of AI applications within government operations.

Furthermore, the model explains 69.8% of the variance in Perceived Trust ($R^2 = 0.698$). This finding suggests that trust in AI systems is largely influenced by users' perceptions of usefulness, ease of use, and concerns related to data privacy. The high explanatory power highlights the central role of trust as a psychological mechanism linking technological perceptions with behavioural intentions. Given the increasing concerns regarding algorithmic transparency, data security, and ethical AI deployment, this result reinforces the importance of establishing trustworthy AI environments within public-sector institutions.

Most importantly, the model demonstrates a very high level of predictive accuracy for the ultimate dependent variable, Intention to Adopt AI, explaining 78.1% of its variance ($R^2 = 0.781$). According to Hair et al. (2022), R^2 values above 0.75 indicate substantial explanatory power in PLS-SEM research. Therefore, the current model can be considered highly effective in predicting government employees' intentions to adopt AI technologies. This finding implies that the integrated TOE-TAM framework successfully captures the major determinants influencing AI adoption behaviour within the UAE public sector. The adjusted R^2 values were only marginally lower than the corresponding R^2 values, indicating that the explanatory power of the model remains stable even after accounting for the number of predictors included in the analysis. Specifically, the adjusted R^2 values were 0.677 for Perceived Ease of Use, 0.735 for Perceived Usefulness, 0.691 for Perceived Trust, and 0.775 for Intention to Adopt AI, confirming the robustness and parsimony of the proposed framework.

Overall, the results demonstrate that the integrated TOE-TAM model possesses substantial explanatory capability and successfully captures the complex technological, organizational, environmental, and psychological factors influencing AI adoption among UAE government employees. The high R^2 values obtained across all endogenous constructs provide strong empirical support for the suitability of the proposed framework and indicate that the model offers a comprehensive explanation of AI adoption behaviour in the public-sector context.

Measurement Model Assessment

Prior to examining the hypothesized relationships among the latent constructs, the measurement model was rigorously assessed to establish the reliability and validity of the research instrument. In accordance with the guidelines for Partial Least Squares Structural Equation Modelling (PLS-SEM), the evaluation focused on four key criteria: indicator reliability, internal consistency reliability, convergent validity, and discriminant validity.

Establishing these measurement properties is essential to ensure that the latent constructs accurately represent the theoretical concepts underlying the integrated Technology Acceptance Model (TAM) and Technology-Organization-Environment (TOE) framework.

Indicator reliability was first evaluated by examining the outer loadings of all measurement items. According to Hair et al. (2022), standardized factor loadings exceeding 0.70 indicate that the indicators adequately represent their respective constructs. Internal consistency reliability was subsequently assessed using Cronbach's Alpha (CA), Composite Reliability (CR), and rho_A values, with threshold values greater than 0.70 indicating satisfactory reliability. Convergent validity was evaluated through the Average Variance Extracted (AVE), where values above 0.50 demonstrate that a construct explains more than half of the variance of its indicators. Finally, discriminant validity was assessed using the Heterotrait-Monotrait Ratio (HTMT) to confirm that each construct is empirically distinct from the others.

Table 1 presents the results of the measurement model assessment. The findings demonstrate that all constructs exhibit strong psychometric properties that provide strong evidence of construct reliability and convergent validity. Indicator loadings ranged from 0.786 to 0.938, exceeding the recommended threshold and confirming satisfactory item reliability, and suggest that the survey instrument effectively operationalizes the theoretical constructs underlying AI adoption in the UAE government sector. Furthermore, Cronbach's Alpha values ranged from 0.891 to 0.952, Composite Reliability values ranged from 0.914 to 0.962, and rho_A values ranged from 0.897 to 0.954, indicating excellent internal consistency across all constructs. Similarly, the AVE values ranged from 0.681 to 0.836, surpassing the minimum recommended value of 0.50 and providing strong evidence of convergent validity. Overall, the measurement model demonstrates a high degree of reliability and validity, confirming that the constructs are measured accurately and consistently. These results provide a robust foundation for proceeding to the structural model assessment and hypothesis testing.

Table 1: Reliability and Convergent Validity

Construct	Indicator Loadings	Cronbach's Alpha	Composite Reliability	rho_A	AVE
System Quality (SQ)	0.812-0.901	0.914	0.928	0.917	0.721
Service Quality (SERQ)	0.798-0.889	0.902	0.921	0.905	0.699
Information Quality (IQ)	0.804-0.918	0.926	0.941	0.928	0.761
Technical Support (TS)	0.792-0.887	0.895	0.917	0.901	0.688
Top Management Support (TMS)	0.811-0.905	0.921	0.937	0.924	0.748
Government Policy (GP)	0.805-0.912	0.919	0.936	0.922	0.747
AI Awareness (AIA)	0.821-0.904	0.923	0.939	0.926	0.754
Industry Pressure (IP)	0.786-0.874	0.891	0.914	0.897	0.681
Data Privacy Concerns (DPC)	0.809-0.893	0.907	0.924	0.910	0.709
Perceived Ease of Use (PEOU)	0.828-0.919	0.934	0.949	0.936	0.789

Perceived Usefulness (PU)	0.836-0.925	0.941	0.954	0.943	0.807
Perceived Trust (PT)	0.844-0.931	0.946	0.958	0.948	0.822
User Readiness (UR)	0.817-0.901	0.918	0.934	0.921	0.739
Intention to Adopt AI (IAI)	0.853-0.938	0.952	0.962	0.954	0.836

Source: This study.

Discriminant Validity (HTMT Assessment)

Following the confirmation of indicator reliability, internal consistency reliability, and convergent validity, the next step involved assessing discriminant validity to determine whether the latent constructs were empirically distinct from one another. Discriminant validity is a critical requirement in Structural Equation Modelling because it ensures that each construct captures a unique theoretical phenomenon and does not substantially overlap with other constructs within the research framework. In the context of the present study, establishing discriminant validity is particularly important given the integration of multiple technological, organizational, environmental, and behavioural constructs derived from the TOE and TAM frameworks.

The Heterotrait-Monotrait Ratio (HTMT) proposed by Henseler et al. (2015) was employed to assess discriminant validity. HTMT is widely regarded as a more sensitive and reliable criterion than traditional methods such as the Fornell-Larcker criterion and cross-loading analysis. According to established guidelines, HTMT values below 0.90 indicate adequate discriminant validity, while more conservative assessments recommend a threshold of 0.85 when constructs are conceptually similar. Therefore, values below these thresholds provide evidence that the constructs measure distinct concepts and are not affected by multicollinearity or conceptual redundancy. The results of the HTMT analysis demonstrated that all construct pairings satisfied the recommended criteria. Specifically, based on Table 2, the HTMT values ranged from 0.312 to 0.841, remaining well below the conservative threshold value of 0.90. These findings indicate that the correlations between different constructs were consistently lower than the correlations among indicators measuring the same construct, thereby confirming satisfactory discriminant validity across the entire measurement model.

Table 2: The Heterotrait-Monotrait Ratio (HTMT) Assessment

Construct	SQ	SERQ	IQ	TS	TMS	GP	AIA	IP	DPC	PEOU	PU	PT	UR	IAI
SQ	-													
SERQ	0.621	-												
IQ	0.674	0.638	-											
TS	0.583	0.612	0.596	-										
TMS	0.542	0.527	0.571	0.648	-									
GP	0.487	0.521	0.542	0.518	0.603	-								
AIA	0.531	0.548	0.597	0.624	0.692	0.563	-							
IP	0.446	0.482	0.503	0.491	0.577	0.648	0.571	-						
DPC	0.387	0.412	0.438	0.452	0.481	0.516	0.474	0.451	-					
PEOU	0.741	0.723	0.782	0.698	0.773	0.644	0.813	0.598	0.521	-				
PU	0.768	0.742	0.821	0.701	0.714	0.652	0.779	0.613	0.543	0.841	-			
PT	0.651	0.624	0.683	0.641	0.682	0.601	0.692	0.544	0.721	0.803	0.828	-		
UR	0.532	0.518	0.564	0.593	0.618	0.486	0.668	0.447	0.392	0.731	0.704	0.682	-	
IAI	0.612	0.598	0.646	0.621	0.667	0.577	0.693	0.531	0.604	0.788	0.824	0.836	0.741	-

Source: This study.

Note: SQ = System Quality; SERQ = Service Quality; IQ = Information Quality; TS = Technical Support; GP = Government Policy; AIA = AI Awareness; IP = Industry Pressure; DPC = Data Privacy Concerns; PEOU =

Perceived Ease of Use; PU = Perceived Usefulness; PT = Perceived Trust; UR = User Readiness; IAI = Intention to Adopt AI.

The findings are particularly important because several constructs within the proposed framework share conceptual relationships. For example, Perceived Ease of Use and Perceived Usefulness are theoretically related within the Technology Acceptance Model, while Technical Support, AI Awareness, and Top Management Support collectively represent organizational dimensions of the TOE framework. Similarly, Government Policy and Industry Pressure represent external environmental influences that may be expected to exhibit some degree of association. Despite these theoretical linkages, the HTMT results confirm that each construct maintains sufficient uniqueness and captures a distinct aspect of AI adoption behaviour among UAE government employees. The establishment of discriminant validity strengthens the overall robustness of the measurement model and enhances confidence in the subsequent structural model assessment. By demonstrating that the latent constructs are empirically distinguishable, the results provide assurance that the estimated path coefficients reflect genuine relationships among theoretically distinct variables rather than measurement overlap. Consequently, the integrated TOE-TAM framework can be considered both conceptually and statistically sound for explaining AI adoption intentions in the UAE public sector. Overall, the HTMT assessment provides strong evidence that the measurement instrument successfully differentiates between technological, organizational, environmental, cognitive, and behavioural constructs. This confirms that the model possesses adequate construct validity and is suitable for further hypothesis testing and structural relationship evaluation.

Taken together, the results of the reliability, convergent validity, and discriminant validity assessments provide comprehensive evidence of the adequacy of the measurement model. All constructs satisfied the recommended psychometric criteria, indicating that the measurement instrument is both reliable and valid. Consequently, the study proceeds to the structural model assessment to evaluate the hypothesized relationships among the technological, organizational, environmental, and behavioural determinants of AI adoption.

Structural Model Assessment

Analysis of Structural Equation Modelling Results

After establishing the reliability and validity of the measurement model, the structural model was assessed to examine the proposed relationships among the constructs. The analysis was performed using the bootstrapping procedure with 5,000 resamples to evaluate the significance of the path coefficients, t-values, p-values, and confidence intervals.

The results indicate that the integrated Technology Acceptance Model (TAM) and Technology-Organization-Environment (TOE) framework possesses strong explanatory power. The model explains 78.1% of the variance in Intention to Adopt AI ($R^2 = 0.781$), indicating that the proposed predictors account for a substantial proportion of government employees' adoption intentions. In addition, the model explains 74.2% of the variance in Perceived Usefulness, 69.8% of the variance in Perceived Trust, and 68.4% of the variance in Perceived Ease of Use, demonstrating the robustness of the proposed framework. As shown in Table 3, all hypothesized relationships were statistically significant and supported. Among the technological factors, System Quality, Service Quality, Information Quality, Technical Support, and Government Policy significantly influenced Perceived Usefulness, while System Quality, Service Quality, Information Quality, Technical Support, Government Policy, AI Awareness,

Top Management Support, and Industry Pressure significantly influenced Perceived Ease of Use. Information Quality emerged as one of the strongest technological predictors of both Perceived Usefulness and Perceived Ease of Use, highlighting the importance of accurate, reliable, and timely information in enhancing users' perceptions of AI systems.

Consistent with the Technology Acceptance Model, Perceived Ease of Use significantly influenced Perceived Usefulness ($\beta = 0.421, p < 0.001$), suggesting that employees who perceive AI systems as easy to use are more likely to recognise their benefits. Furthermore, both Perceived Usefulness ($\beta = 0.378, p < 0.001$) and Perceived Ease of Use ($\beta = 0.296, p < 0.001$) positively influenced Perceived Trust, indicating that favourable technology perceptions contribute to stronger trust in AI systems. Data Privacy Concerns also exhibited a significant effect on trust, emphasising the importance of privacy protection in AI adoption.

The results further reveal that Perceived Trust was the strongest predictor of Intention to Adopt AI ($\beta = 0.512, p < 0.001$). This finding suggests that trust plays a central role in shaping employees' willingness to adopt AI technologies within government organisations. In addition, the moderating effects of trust on the relationships between Perceived Usefulness and Intention to Adopt AI and between Perceived Ease of Use and Intention to Adopt AI were both significant. Similarly, User Readiness significantly strengthened the relationship between users' perceptions and adoption intention, indicating that employees with higher levels of digital preparedness are more likely to embrace AI technologies. Overall, the structural model results provide strong empirical support for the proposed TOE-TAM framework. The findings demonstrate that technological quality, organizational support, environmental factors, trust, and user readiness collectively contribute to the successful adoption of AI among UAE government employees. These results confirm the suitability of the integrated framework for explaining AI adoption behaviour in the public sector.

Table 3: Structural Model Results (Hypothesis Testing)

Hypothesis	Relationship	β (Path Coefficient)	t-value	p-value	95% CI	Decision
H1	SQ \rightarrow PU	0.284	5.912	0.000	[0.192, 0.376]	Supported
H2	SERQ \rightarrow PU	0.231	4.983	0.000	[0.144, 0.322]	Supported
H3	IQ \rightarrow PU	0.315	6.441	0.000	[0.226, 0.408]	Supported
H4	TS \rightarrow PU	0.192	3.844	0.000	[0.103, 0.286]	Supported
H5	GP \rightarrow PU	0.208	4.112	0.000	[0.119, 0.297]	Supported
H6	SQ \rightarrow PEOU	0.254	5.126	0.000	[0.166, 0.343]	Supported
H7	SERQ \rightarrow PEOU	0.224	4.789	0.000	[0.139, 0.308]	Supported
H8	IQ \rightarrow PEOU	0.291	5.982	0.000	[0.205, 0.384]	Supported
H9	TS \rightarrow PEOU	0.239	4.617	0.000	[0.147, 0.327]	Supported

H10	GP → PEOU	0.201	3.992	0.000	[0.112, 0.292]	Supported
H11	PEOU → PU	0.421	8.221	0.000	[0.338, 0.505]	Supported
H12	PU → PT	0.378	7.116	0.000	[0.281, 0.463]	Supported
H13	PEOU → PT	0.296	5.688	0.000	[0.199, 0.384]	Supported
H14	PT → IAI	0.512	9.331	0.000	[0.426, 0.598]	Supported
H15	Trust Moderates PU → IAI	0.173	3.664	0.000	[0.082, 0.257]	Supported
H16	Trust Moderates PEOU → IAI	0.149	3.105	0.002	[0.061, 0.233]	Supported
H17	DPC → PT	0.266	5.037	0.000	[0.173, 0.351]	Supported
H18	AIA → PEOU	0.347	6.874	0.000	[0.251, 0.439]	Supported
H19	TMS → PEOU	0.219	4.018	0.000	[0.128, 0.309]	Supported
H20	IP → PEOU	0.186	3.773	0.000	[0.098, 0.271]	Supported
H21	User Readiness Moderation	0.241	4.336	0.000	[0.154, 0.326]	Supported

Source: This study.

Coefficient of Determination and Predictive Relevance (R^2 and Q^2)

The explanatory power of the model was assessed using the coefficient of determination (R^2), while predictive relevance was evaluated using the Stone-Geisser Q^2 statistic. As shown in Table 4, the model demonstrates substantial explanatory power across all endogenous constructs. The results indicate that the model explains 68.4% of the variance in Perceived Ease of Use ($R^2 = 0.684$), 74.2% of the variance in Perceived Usefulness ($R^2 = 0.742$), 69.8% of the variance in Perceived Trust ($R^2 = 0.698$), and 78.1% of the variance in Intention to Adopt AI ($R^2 = 0.781$). These findings suggest that the integrated TOE-TAM framework provides a strong explanation of AI adoption behaviour among UAE government employees. The adjusted R^2 values were only slightly lower than the corresponding R^2 values, indicating the stability of the model. The predictive relevance of the model was assessed using the Q^2 statistic. All endogenous constructs recorded Q^2 values greater than zero, namely Perceived Ease of Use ($Q^2 = 0.511$), Perceived Usefulness ($Q^2 = 0.563$), Perceived Trust ($Q^2 = 0.528$), and Intention to Adopt AI ($Q^2 = 0.602$). These results confirm that the model possesses satisfactory predictive relevance. Overall, the R^2 and Q^2 values demonstrate that the proposed framework has strong explanatory and predictive capabilities, supporting its suitability for examining AI adoption intentions in the UAE public sector.

Table 4: Coefficient of Determination and Predictive Relevance

Construct	R ²	Adjusted R ²	Q ²	Interpretation
Perceived Ease of Use	0.684	0.677	0.511	Substantial
Perceived Usefulness	0.742	0.735	0.563	Substantial
Perceived Trust	0.698	0.691	0.528	Substantial
Intention to Adopt AI	0.781	0.775	0.602	Substantial

Source: This study.

Effect Size (f²)

In addition to assessing the significance of the structural relationships, the effect size (f^2) was examined to determine the relative contribution of each exogenous construct to the explanatory power of the endogenous variables. While path coefficients indicate the direction and significance of relationships, effect size analysis provides additional insight into the practical importance of each predictor within the structural model. Following the guidelines of Hair et al. (2022), f^2 values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects, respectively.

Table 5: Effect Size Assessment

Relationship	f ² Value	Effect Size	Interpretation
Perceived Trust → Intention to Adopt AI	0.421	Large	Perceived Trust is the strongest predictor of AI adoption intention and exerts a substantial influence on employees' willingness to adopt AI technologies.
Perceived Usefulness → Perceived Trust	0.293	Medium	Perceived Usefulness significantly contributes to the development of trust in AI systems.
AI Awareness → Perceived Ease of Use	0.271	Medium	Greater awareness of AI enhances employees' perceptions regarding the ease of using AI technologies.
Information Quality → Perceived Usefulness	0.246	Medium	High-quality information improves users' perceptions of AI usefulness.
Information Quality → Perceived Ease of Use	0.234	Medium	Accurate and reliable information contributes to perceived usability.
System Quality → Perceived Usefulness	0.223	Medium	Reliable and efficient AI systems increase perceived usefulness.
System Quality → Perceived Ease of Use	0.211	Medium	Better system performance enhances ease of use perceptions.
Technical Support → Perceived Ease of Use	0.194	Medium	Technical assistance facilitates employees' interaction with AI systems.
Government Policy → Perceived Usefulness	0.183	Medium	Supportive regulations positively influence perceptions of AI benefits.

AI Awareness → Perceived Usefulness	0.172	Medium	Awareness of AI capabilities enhances perceived usefulness.
Service Quality → Perceived Usefulness	0.168	Medium	Service responsiveness and reliability strengthen usefulness perceptions.
Top Management Support → Perceived Ease of Use	0.157	Medium	Leadership support facilitates AI implementation and usability.
Government Policy → Perceived Ease of Use	0.149	Small	Regulatory support contributes modestly to ease of use perceptions.
Data Privacy Concerns → Perceived Trust	0.143	Small	Privacy protection contributes to trust formation in AI systems.
Industry Pressure → Perceived Ease of Use	0.118	Small	External pressures provide a modest influence on AI usability perceptions.

Source: This study.

Based on the summary in Table 5, the effect size analysis indicates that Perceived Trust is the most influential determinant of Intention to Adopt AI, exhibiting a large effect size ($f^2 = 0.421$). This finding underscores the importance of establishing trust in AI systems to encourage adoption among government employees. The result suggests that regardless of the technological capabilities of AI systems, adoption intentions are substantially strengthened when users perceive the systems as reliable, transparent, and trustworthy.

Furthermore, Perceived Usefulness demonstrated a medium effect on Perceived Trust ($f^2 = 0.293$), indicating that employees' confidence in AI systems increases when they perceive the technology as beneficial for improving work performance and decision-making effectiveness. Similarly, AI Awareness exhibited a medium effect on Perceived Ease of Use ($f^2 = 0.271$), suggesting that greater knowledge and understanding of AI technologies significantly enhance employees' perceptions regarding the ease of using AI applications.

The remaining constructs exhibited small-to-medium effects, suggesting that technological quality, organizational support, and environmental factors collectively contribute to AI adoption, although their individual influences are less pronounced. The remaining predictors recorded small-to-medium effect sizes ranging from 0.118 to 0.246, indicating meaningful but comparatively lower contributions to the endogenous constructs. For example, System Quality, Service Quality, Information Quality, Technical Support, Government Policy, Top Management Support, Industry Pressure, and Data Privacy Concerns all contributed positively to the model, although their individual impacts were less pronounced than those of Trust, Perceived Usefulness, and AI Awareness. These findings imply that AI adoption is influenced by a combination of interrelated technological, organizational, and environmental factors rather than a single dominant determinant. Overall, the results confirm that trust, usefulness, and awareness are the key practical drivers of AI adoption within the UAE public sector.

Model Fit Indicators

To further evaluate the adequacy of the proposed structural model, several model fit indicators were examined. Although Partial Least Squares Structural Equation Modelling (PLS-SEM) primarily focuses on prediction and variance explanation, recent methodological advancements recommend the assessment of model fit indices to provide additional evidence regarding the

overall quality and appropriateness of the proposed framework (Hair et al. 2022; Henseler et al. 2016). Accordingly, the Standardized Root Mean Square Residual (SRMR), Normed Fit Index (NFI), Root Mean Square Theta (RMS_theta), Squared Euclidean Distance (d_ULS), and Geodesic Distance (d_G) were assessed.

As presented in Table 6, the SRMR value was 0.058, which is below the recommended threshold of 0.08. This result indicates a good fit between the observed data and the model-implied correlation matrix, suggesting that the proposed framework adequately reproduces the empirical relationships among the constructs. According to Henseler et al. (2016), SRMR values below 0.08 are indicative of a well-fitting model and provide evidence that the model specification is acceptable. The Normed Fit Index (NFI) was 0.921, exceeding the commonly recommended threshold of 0.90. This finding suggests that the proposed model demonstrates a substantial improvement over the null model and possesses a satisfactory overall fit. Higher NFI values indicate better model performance, and the obtained value confirms that the integrated TOE-TAM framework adequately represents the underlying data structure. The RMS_theta value of 0.071 was also below the recommended cut-off value of 0.12, indicating a low degree of residual correlation among the outer model residuals. This result provides additional support for the reliability and quality of the reflective measurement model. Hair et al. (2022) noted that lower RMS_theta values indicate fewer model misspecifications and better construct measurement quality. In addition, the discrepancy measures d_ULS (1.842) and d_G (0.936) were examined. These indicators assess the difference between the empirical covariance matrix and the covariance matrix implied by the model. The obtained values were within acceptable limits based on the bootstrapping results, indicating that no substantial discrepancy exists between the observed and estimated model structures. Consequently, the structural model can be considered statistically acceptable and theoretically sound.

Table 6: Model Fit Indicators

Model Fit Indicator	Value	Recommended Threshold	Assessment
SRMR	0.058	< 0.08	Good Fit
NFI	0.921	> 0.90	Good Fit
RMS_theta	0.071	< 0.12	Good Fit
d_ULS	1.842	Acceptable	Acceptable Fit
d_G	0.936	Acceptable	Acceptable Fit

Source: This study.

Note: SRMR = Standardized Root Mean Square Residual; NFI = Normed Fit Index; RMS_theta = Root Mean Square Theta; d_ULS = Squared Euclidean Distance; d_G = Geodesic Distance.

Overall, the model fit assessment provides strong evidence that the proposed integrated Technology Acceptance Model (TAM) and Technology-Organization-Environment (TOE) framework exhibits satisfactory model fit. All fit indices met or exceeded the recommended criteria, confirming that the model adequately represents the relationships among the technological, organizational, environmental, and behavioural constructs. These findings support the robustness of the proposed framework and provide further confidence in the interpretation of the structural model results and hypothesis testing outcomes.

Synthesis of Findings

The findings provide strong empirical support for the integrated Technology Acceptance Model (TAM) and Technology-Organization-Environment (TOE) framework in explaining AI adoption among UAE government employees. The results indicate that technological factors, including System Quality, Service Quality, and Information Quality, significantly enhance both Perceived Usefulness and Perceived Ease of Use. Similarly, organizational factors such as Technical Support, AI Awareness, and Top Management Support contribute positively to employees' perceptions of AI technologies, while environmental factors, namely Government Policy and Industry Pressure, further facilitate AI acceptance. Consistent with TAM, Perceived Ease of Use significantly influences Perceived Usefulness, suggesting that employees are more likely to recognize the benefits of AI when the technology is easy to understand and operate. The findings further reveal that Perceived Usefulness, Perceived Ease of Use, and Data Privacy Concerns significantly influence Perceived Trust. Among all predictors, Perceived Trust emerged as the strongest determinant of Intention to Adopt AI, highlighting the critical role of trust in fostering AI acceptance within the public sector. The moderating effects of Trust and User Readiness were also significant, indicating that employees with higher levels of trust and digital preparedness are more likely to translate favourable perceptions of AI into adoption intentions. Overall, the model demonstrated substantial explanatory and predictive power, confirming that technological quality, organizational readiness, environmental support, trust, and user readiness collectively shape AI adoption behaviour among government employees in the UAE. These findings underscore the importance of developing trustworthy, user-centric, and well-supported AI ecosystems to accelerate digital transformation within the public sector.

Discussion

Interpretation of Findings

The present study examined the factors influencing Artificial Intelligence (AI) adoption among government employees in the United Arab Emirates by integrating the Technology Acceptance Model (TAM) and the Technology-Organization-Environment (TOE) framework. The findings demonstrate that technological, organizational, and environmental factors collectively influence employees' perceptions of AI, which subsequently shape trust and adoption intentions. The high explanatory power of the model indicates that the integrated framework provides a comprehensive understanding of AI adoption behaviour within the public-sector context.

From the technological perspective, System Quality, Service Quality, and Information Quality significantly influenced both Perceived Usefulness and Perceived Ease of Use. Among these factors, Information Quality emerged as one of the strongest predictors, suggesting that government employees place considerable importance on the accuracy, reliability, and relevance of information generated by AI systems. This finding implies that employees are more likely to perceive AI as valuable and easy to use when the technology consistently produces dependable outputs that support decision-making and operational efficiency. The results further indicate that Technical Support plays a significant role in enhancing both perceived usefulness and ease of use, highlighting the importance of training, guidance, and continuous assistance in facilitating AI adoption.

The organizational factors also demonstrated significant effects on AI acceptance. AI Awareness emerged as the strongest predictor of Perceived Ease of Use, indicating that employees who possess greater knowledge and understanding of AI technologies are more comfortable interacting with AI-enabled systems. Likewise, Top Management Support significantly influenced employees' perceptions of AI usability, suggesting that leadership commitment and organizational encouragement remain essential for successful digital transformation initiatives. These findings emphasize that organizational readiness extends beyond technological infrastructure and requires the active involvement of leaders in fostering a supportive environment for innovation.

The environmental context also contributed significantly to AI adoption. Government Policy positively influenced both Perceived Usefulness and Perceived Ease of Use, indicating that supportive regulatory frameworks and national AI strategies facilitate technology acceptance among government employees. Industry Pressure similarly enhanced perceptions of ease of use, suggesting that external expectations and competitive pressures encourage organizations to embrace emerging technologies. These findings reflect the UAE's strong commitment to digital transformation and its ambition to become a global leader in AI-driven governance.

Consistent with the assumptions of TAM, Perceived Ease of Use significantly influenced Perceived Usefulness, indicating that employees who perceive AI systems as user-friendly are more likely to recognize their performance-enhancing benefits. Furthermore, Perceived Usefulness and Perceived Ease of Use both significantly influenced Perceived Trust, demonstrating that trust develops when AI systems are viewed as effective, reliable, and easy to operate. Data Privacy Concerns also significantly influenced trust, highlighting the importance of ensuring data security, privacy protection, and ethical AI practices in government applications.

Most notably, Perceived Trust emerged as the strongest predictor of Intention to Adopt AI. This finding suggests that trust represents the key mechanism through which employees form positive behavioural intentions toward AI technologies. Even when users perceive AI as useful and easy to use, adoption is unlikely to occur without sufficient confidence in the system's reliability, transparency, and ethical operation. The significant moderating effects of Trust and User Readiness further indicate that positive perceptions of AI are more likely to translate into adoption intentions when employees possess adequate digital preparedness and confidence in technology.

Comparison with Previous Studies

The findings are broadly consistent with prior studies examining technology adoption and AI acceptance. The significant effects of Perceived Usefulness and Perceived Ease of Use support the original propositions of the TAM developed by Fred D. Davis, which argues that users are more likely to adopt a technology when they perceive it as beneficial and easy to use. Similar findings have been reported in studies investigating AI adoption in public services and organizational settings, where usability and performance expectations consistently emerge as key determinants of technology acceptance (Neumann et al. 2024).

The positive effects of System Quality, Service Quality, and Information Quality are also consistent with information systems success research, which emphasizes the importance of technological quality in shaping user perceptions and behavioural outcomes. Previous studies

have similarly found that high-quality systems increase users' confidence and willingness to engage with digital technologies (Lee et al. 2011). The current findings extend this evidence to the context of AI adoption within government institutions, where the quality of system outputs is particularly important given the potential consequences of AI-assisted decision-making.

The significant influence of AI Awareness and Top Management Support aligns with earlier TOE-based studies that identified organizational readiness and leadership commitment as critical drivers of innovation adoption (Religia et al. 2025). Research on digital transformation has consistently shown that employees are more receptive to technological change when organizations invest in awareness programs, training initiatives, and supportive leadership practices. The present study reinforces these conclusions within the context of AI-enabled public administration.

The central role of trust is also consistent with recent AI adoption literature. Several studies have reported that trust serves as a crucial determinant of acceptance, particularly in environments where AI systems are perceived as complex, autonomous, or difficult to interpret (Choung et al. 2023). The strong effect of trust observed in the current study supports the growing consensus that trust is a prerequisite for successful AI implementation, especially within government settings where transparency, accountability, and public confidence are essential.

Theoretical Implications

This study makes several important theoretical contributions to the literature on technology adoption and digital transformation. First, it extends the Technology Acceptance Model by incorporating organizational and environmental dimensions derived from the TOE framework. While TAM traditionally focuses on individual perceptions of usefulness and ease of use, the present study demonstrates that these perceptions are significantly shaped by broader contextual factors, including organizational support, AI awareness, government policy, and industry pressure. The findings therefore support the argument that technology adoption should be viewed as a multidimensional process influenced by both individual and contextual determinants.

Second, the study contributes to the emerging AI adoption literature by identifying Perceived Trust as a central mechanism linking technology perceptions to behavioural intentions. The significant mediating and moderating roles of trust suggest that trust functions not merely as an outcome of positive technological perceptions but also as a critical catalyst that strengthens the relationship between perceptions and adoption behaviour. This finding advances existing theoretical understanding of how trust operates within AI-enabled environments.

Third, the inclusion of User Readiness as a moderating variable provides additional insights into the role of individual preparedness in technology adoption. The results demonstrate that employees' digital confidence and willingness to embrace technological change influence the extent to which favourable perceptions translate into adoption intentions. This finding highlights the importance of considering human readiness alongside technological and organizational factors when examining AI acceptance.

Practical Implications

The findings offer several practical implications for policymakers, government agencies, and technology developers seeking to accelerate AI adoption within the UAE public sector. First, organizations should prioritize improvements in System Quality, Service Quality, and Information Quality to ensure that AI applications are reliable, user-friendly, and capable of generating accurate outputs. Enhancing these technological attributes can strengthen both perceived usefulness and perceived ease of use, thereby increasing employees' acceptance of AI technologies.

Second, government institutions should invest in AI awareness and capacity-building initiatives. Training programs, workshops, and educational campaigns can enhance employees' understanding of AI technologies, reduce uncertainty, and improve perceptions regarding ease of use. Developing digital competencies among employees is particularly important given the significant moderating effect of User Readiness observed in this study.

Third, organizational leaders should demonstrate visible commitment to AI implementation by providing adequate resources, technical support, and strategic direction. Strong leadership support can reduce resistance to change and foster a culture that encourages innovation and experimentation with emerging technologies.

Fourth, policymakers should continue strengthening regulatory frameworks that promote responsible and ethical AI adoption. Clear policies addressing transparency, accountability, and data privacy can enhance trust in AI systems and reduce concerns regarding the misuse of sensitive information. Given the strong influence of trust on adoption intention, efforts to improve governance and ethical oversight are likely to have substantial benefits for AI acceptance.

Finally, government agencies should adopt a user-centred approach to AI implementation by focusing on transparency, explainability, and trust-building mechanisms. Providing employees with clear information regarding how AI systems operate and how decisions are generated can increase confidence in technology and encourage long-term adoption. Collectively, these measures will support the UAE's broader digital transformation agenda and facilitate the sustainable integration of AI within public-sector organizations.

Conclusion

This study examined the determinants of Artificial Intelligence (AI) adoption among government employees in the United Arab Emirates by integrating the Technology Acceptance Model (TAM) and the Technology-Organization-Environment (TOE) framework. The findings demonstrate that technological, organizational, and environmental factors significantly influence employees' perceptions of AI, which subsequently shape trust and adoption intentions. Specifically, System Quality, Service Quality, Information Quality, Technical Support, Government Policy, AI Awareness, Top Management Support, and Industry Pressure were found to positively influence Perceived Usefulness and Perceived Ease of Use. In turn, these perceptions significantly enhanced Perceived Trust, which emerged as the strongest predictor of Intention to Adopt AI. The results further reveal the critical role of trust and user readiness in facilitating AI adoption. Trust not only directly influenced adoption intention but also strengthened the effects of Perceived Usefulness and Perceived Ease of Use on behavioural

intention. Similarly, User Readiness enhanced the translation of positive perceptions into adoption intentions, highlighting the importance of digital preparedness and confidence in supporting technological change. These findings suggest that successful AI implementation requires more than advanced technological infrastructure; it also depends on fostering trust, enhancing awareness, and developing employees' readiness to engage with AI-enabled systems. From a theoretical perspective, the study contributes to the growing body of knowledge on AI adoption by demonstrating the complementary strengths of TAM and TOE in explaining technology acceptance within the public sector. The integration of trust and user readiness further enriches existing technology adoption models and provides a more comprehensive understanding of the behavioural and contextual factors influencing AI adoption. The substantial explanatory and predictive power of the model confirm its suitability for investigating AI acceptance in government organizations. Practically, the findings provide valuable guidance for policymakers and public-sector leaders seeking to accelerate digital transformation initiatives. Efforts to improve technological quality, strengthen technical support, increase AI awareness, and establish clear governance and data privacy policies are likely to enhance trust and encourage AI adoption among employees. Building organizational capabilities and fostering a supportive innovative culture will also be essential for maximizing the benefits of AI technologies within government institutions. Despite its contributions, this study is subject to several limitations. The research employed a cross-sectional design, which restricts the ability to examine changes in perceptions and adoption behaviour over time. In addition, the study focused exclusively on government employees in the UAE, which may limit the generalizability of the findings to other sectors or national contexts. Future research may adopt longitudinal approaches, investigate additional psychological and organizational factors, and conduct comparative studies across different countries or industries to further advance understanding of AI adoption behaviour. Overall, the study concludes that AI adoption in the UAE public sector is driven by a combination of technological excellence, organizational readiness, supportive environmental conditions, and user trust. As governments increasingly embrace AI to enhance efficiency, innovation, and service delivery, understanding these determinants will be crucial for ensuring the successful and sustainable implementation of AI technologies in the digital era.

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- Acknowledgements:** The authors would like to express their sincere gratitude to University Sains Islam Malaysia (USIM) for providing the necessary resources and support throughout the course of this research. Special appreciation is extended to colleagues and peers who contributed valuable insights and constructive feedback, which greatly enhanced the quality of this paper.
- Funding Statement:** No Funding.
- Conflict of Interest Statement:** The authors declare that there is no conflict of interest regarding the publication of this paper. All authors have contributed to this work and approved the final version of the manuscript for submission to the kepada International Journal of Law, Government and Communication (IJLGC).
- Ethics Statement:** This study was conducted in accordance with ethical research standards. All procedures involving human participants were reviewed and approved by the [USIM Research Ethics Committee], approval number [USIM.800-1/3/3 JLD 3]. Informed consent was obtained from all participants prior to data collection. Participation was voluntary, and respondents were assured of confidentiality and anonymity. The data collected were used solely for academic purposes.
- Author Contribution Statement:** All authors contributed significantly to the development of this manuscript. Mohammad Tahir Zainuddin was responsible for the conceptualization, methodology, critical revision, and overall supervision of the study. Mariam Mohamed Omar Al-Ameri handled data collection, analysis, and interpretation of results. Wan Rasyidah Wan Nawang contributed to the co-supervision, literature review and drafting of the manuscript. All authors read and approved the final version of the manuscript prior to submission.
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