INTERNATIONAL JOURNAL OF ACADEMIC RESEARCH IN BUSINESS & SOCIAL SCIENCES

Vol 16, Issue 3, (2026) E-ISSN: 2222-6990

AI Adoption among the UAE's Government Servants: An Empirical Model Analysis

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DOI Link: http://dx.doi.org/10.6007/IJARBSS/v16-i3/27850

Published Date: 07 March 2026

Abstract

This study presents a preliminary validation and reliability assessment of measurement constructs used to examine artificial intelligence (AI) adoption among government servants in the United Arab Emirates (UAE), grounded in the Technology Acceptance Model (TAM) and the Technology–Organization–Environment (TOE) framework. The objective is to evaluate the suitability and internal consistency of the adapted instrument before proceeding to the main study. A pilot test was conducted involving 32 UAE government servants selected through convenience sampling. Data were analysed using the Statistical Package for the Social Sciences (SPSS) version 27.0. Reliability of the constructs was assessed using Cronbach's alpha, while correlation analysis was performed to provide preliminary evidence of construct relationships and instrument coherence. The results indicate that all constructs achieved Cronbach's alpha values exceeding the recommended threshold of 0.70, demonstrating satisfactory internal consistency. Correlation findings further suggest acceptable relationships among constructs, supporting the instrument's preliminary convergent validity without indicating problematic multicollinearity. These findings confirm that the TAM–TOE measurement scales are reliable and appropriate for investigating AI adoption in the UAE public sector context. The study contributes methodologically by establishing an empirically tested instrument for subsequent large-scale data collection and structural modelling, thereby enhancing the robustness of future research on AI adoption within government institutions.

Keywords: Artificial Intelligence Adoption, Public Sector Innovation, Technology Acceptance Model (TAM–TOE), Consumer Behaviour

Introduction

Adopting artificial intelligence (AI) is a desirable tool for users (Venkatesh, 2022). The use of AI systems has increased dramatically in recent years (Burlakov et al., 2020). Ransbotham et al., (2017) found that 36% of organizations had neither developed nor adopted any AI strategies, while 19% of organizations worldwide had adopted AI strategies and had begun implementing AI-based systems. Additionally, 45% of organizations had looked into or were piloting AI systems in their businesses. The United Arab Emirates (UAE) is recognized for its rapid technological evolution and stands at the forefront of adopting and leveraging the potential of AI (Al Tawhidi & Bourini, 2024).

According to the report from Trendresearch (2025), the UAE artificial intelligence market is projected to surge from roughly USD 3.47 billion in 2023 to over USD 46 billion by 2030, driven by the nation's ambitious National AI Strategy 2031. In the same vein, the AI for healthcare payer market in the UAE is expected to reach a projected revenue of USD28.8 million by 2030. CAGR of 10% is expected of the UAE healthcare payer market from 2024 to 2030. Notable studies have focused attention on determinants of AI in the UAE. For instance, Eybers (2025) looked into the critical success factors (CSFs) that affect the UAE public sector's decision to purchase an AI system. According to this study, the most significant CSF is a clear needs assessment, whilst the least significant one is the long-term value of AI services or systems.

Recent years have witnessed an unprecedented surge in the integration of AI technology, catalysing transformative changes across diverse global industries. Users of AI have been described as those individuals who see the value that technology can bring, particularly to improve their daily lives, and are willing to buy into it (Soni et al. 2019). AI has changed the way people work, play, eat, sleep, and even interact with one another. AI is progressively influencing organizational culture, given the pervasiveness of AI in consumers' lives (Parida et al., 2024). As such, human error is an identified problem (Soni et al. 2019) facing industrial development. To this end, marketing network, payment systems and logistics management are potential sectors to be affected as a result of non-use of artificial intelligence. Therefore, users of AI, use robots to carry out operations that ordinarily require human intelligence, such as learning, thinking, and decision-making, in order to overcome human error (Hussain et al., 2024).

Nevertheless, a number of ethical questions have been raised regarding the design, development, implementation and adoption of AI systems in the adoption sectors, despite the fact that these systems have transformed users behaviour and functionalities, including autonomous objects, speech, image, video recognition, and languages; over sectorial analysis, inefficiencies, corruption, and a lack of transparency are common issues in industrial sectors, result in considerable economic losses and eroding trust (McCormack et al., 2025). The procedure is usually bureaucratic, lengthy, and complicated, making it susceptible to human mistakes and manipulation. Inadequate monitoring mechanisms allow for overpricing, partiality, and resource misallocation, while the sheer volume of data and documentation can overwhelm traditional control measures (Alshehhi et al., 2024). Furthermore, limiting access to information quality, system quality, services quality, technical support and government policies can stifle competition, resulting in inferior outcomes for public sector initiatives.

In the same vein, critics have expressed concerns about the safety and the risk of AI. There are more realistic risks involved in the application of AI (Alzubaidi et al., 2023). This is because, AI is created for specific tasks. Hence, this can be partly becoming dangerous for humans. In lieu of this, trusting the use of the application as well as its usefulness continue to raise critical questions as numerous studies suggested that taken examination into Technology of Acceptance Model (TAM) and Technology Organizational Environment (TOE). Factors such as perceived usefulness and perceived ease of use to use AI plays important role in attitude guiding the adoption of the technology (Alkaabi et al., 2025).

Due to AI's lower interpretability and comprehension compared to other statistical models; the estimating method used by these systems is characterized by complex mechanisms. Bathaee (2017) asserts that there are no profound explanations for how AI systems make decisions. According to the black box paradigm, AI predictions and judgments are comparable to those made by humans. Although AI systems might exhibit bias towards recognizable human patterns, it is conceivable that comprehending them is akin to attempting to identify other highly intelligent creatures. Consequently, the identified gaps left out what are the determinants of contemporary artificial intelligence systems in UAE.

In view of the fact that there is a dearth of literature on the determinant factors for the adoption of AI as well as the role of the ease of use of the AI tools and the usefulness derived therefrom by adopters in the UAE and also because there is scarce literature on how perceived risk from AI use and the trust in AI impact consumers intention to utilize and adopt AI technology in the commercial sectors in the UAE. This study thus, aims to address these gaps and answer the following research questions with these objectives as guides.

Literature Review

Technology Acceptance Model (TAM)

Davis's Technology Acceptance Model (TAM), serves as a foundational element for this study, focusing on users' acceptance of technology. The theory was created to investigate how people accept technology and demonstrate their capacity to do so based on behavioural science principles in sociology and psychology and how those concepts affect technology use (Mantello et al., 2023). It is a commonly adopted model to observe user acceptance and usage of new technologies worldwide. In order to forecast technology's behaviour and offer a theoretical justification for its successful deployment, TAM's main goal was to illuminate the mechanisms behind technology adoption. TAM's practical goal was to educate practitioners on potential actions they may take before putting systems in place. A number of actions were taken in order to achieve the theory's goals (Davis, 1989; Davis, 1993). In order to build the model of technology acceptance, Davis first framed the mechanisms that mediate the relationship between actual system uses and information system (IS) characteristics.

The model was founded on the TRA, which at the time was absent from the IS literature and offered a psychological viewpoint on human behaviour (Davis, 1989; Davis, 1993). This model emphasizes perceived usefulness and perceived ease of use as pivotal determinants of user acceptance. Perceived ease of use is said to be the extent to which an individual believes that using a particular technology will be effortless while perceived usefulness is the degree to which an individual believes that using a particular technology would enhance his person significantly (Davis, 1986). Several studies created, pre-tested, and validated multi-item measures for perceived usefulness and ease of use based on previous empirical literature on human behaviour and information system management. Evidence from earlier studies (Johnson & Payne, 1985; Payne, 1982; Robey, 1979). According to the research, a person's choice to engage in a behaviour is determined by weighing the expected benefits of the behaviour against the costs and effort required to carry it out (Johnson & Payne, 1985; Payne, 1982). Accordingly, an assessment of the trade-off between the system's perceived utility and perceived difficulty of use determines whether or not the information system is used (Davis, 1989).

TAM breaks down technology acceptance into three stages: external factors (system design features) cause cognitive responses (perceived usefulness and perceived ease of use), which in turn create an effective response (attitude toward intention and using technology), which in turn influences use behaviour (Davis, 1989; Davis, 1993). Applying the theory to AI technology, it helps elucidate how consumers in the commercial sector in the UAE adopt AI technology as a result of its perceived usefulness and perceived ease of use. Conversely, the variables of perceived ease of use and perceived usefulness are derived from this model which will be used to test the viability of these variables among the respondents.

Technology-Organization-Environment (TOE)

Technology-Organization-Environment (TOE) framework is a conceptual model used to study the adoption and implementation of technology in organizations. It was first introduced by Tornatzky and Fleischer in 1990. It explains factors that contribute to decision-making in technology adoption at the organizational level. The study argues that in addition to technology, other relevant factors are involved in the adoption of innovations (Tornatzky & Fleischer, 1990). The framework brings together technological, organizational and environmental dimensions to investigate firms' adoption and implementation of technological innovations. TOE has been widely theoretically and empirically examined, and subsequently employed, in sectors such as IT, manufacturing, healthcare, hospitality and financial services (Gamal, 2010; Oliveira & Martins, 2011) to understand organizations' adoption of new technologies. The technological dimension explores all the available internal and external technological equipment, process and practices related to the firm.

Almuraqab et. al (2023) submitted that the UAE, being a developing country, is expected to adopt AI ethically, especially in the e-commerce industry, hence, their study to find out about the ethical issues affecting the adoption of AI technology in the UAE. For this purpose, they conducted a comprehensive assessment of research that has been conducted in the UAE and around the world to investigate ethical considerations pertaining to user data utilization in advertisements. A total of fifty-seven publications about AI and e-commerce were found to be pertinent. Reverse and forward reverse checks were employed to ensure the efficacy of the studies, and iteration was utilized to remove items that were not pertinent to the investigation. The use of AI in the UAE's e-commerce sector and its implications for the business environment are also reviewed in this study. This assessment process shows that during the past few years, the UAE has ethically embraced AI in e-commerce. The report does, however, also highlight the many complicated issues and challenges that the e-commerce sector in the UAE is dealing with, such as the Internet of Things' (IoT) role, Big Data analytics, and ethical issues like privacy concerns. Notable is the government's role in the process, which can shift the game by reacting to legislation and policy direction.

Lund et al., (2023) opined that governmental authorities in Sweden that deal with large volumes of text documents are interested in natural language processing models, a subfield of artificial intelligence, and have begun incorporating it into their organizations due to its potential and the fact that AI is becoming more and more valuable to many organizations worldwide. This made them decide to examine and talk about the elements that affect how government agencies use AI, emphasizing the ethical considerations that are crucial to the adoption process. This is investigated through a survey of the literature, which results in a framework based on the TOE framework. Project managers and AI architects at governmental agencies that work with language models were interviewed to validate the framework. The findings demonstrate that the TOE framework is appropriate for governmental bodies to use when analysing AI adoption. Relative advantage, compatibility and complexity, management support, staff capacity, regulatory environment, and cooperation are the factors that are determined to be significant. Moreover, the results indicate that data access and AI ethics matter in the three domains of technology, organization, and environment.

Intention to Adopt AI

The factors responsible for AI technology are the ones that necessitate such technology. Some of the factors include the need to make life easier for the people, the need to reduce the cost of production and utilities, and modernization, among others. Like every innovation, accepting AI technology is not a given as people usually express reservations before they accept it. This necessitated the division of people into different categories according to the timeliness of their adoption of the technology. The timelines of adoption of AI technology are further exemplified by the categorization of people based on their rate of adoption of the innovation (McElheran et al., 2024). This is usually informed by factors such as the characteristics of the technology, the medium through which they would use the technology, the social influence as well as the attributes of the people adopting it. The attractiveness of these technologies is influenced by elements like connecting capabilities, accessibility, and ease of use (Al-shanableh et al., 2025). Similarly, Izzaty & Shahrom (2025) observed that government and senior management backing have a major impact on the adoption of AI in publicly traded manufacturing enterprises in Malaysia just as Silva et al., (2023) findings indicated that customers' intentions to use chatbots are significantly positively influenced by their perceptions of the chatbots' perceived utility, intelligence, and simplicity of use. In the same vein, Horani et al., (2025) concluded that Relative advantage, compatibility and complexity, management support, staff capacity, regulatory environment, and cooperation are determined to be crucial factors responsible for adopting AI technology.

Based on the literature review discussed above, the following hypotheses have been proposed for the study:

H1: System quality has a positive influence on perceived usefulness of AI.
H2: Service quality has a positive influence on perceived usefulness of AI.
H3: Information quality has a positive influence on the perceived usefulness of AI.
H4: Technical support has a positive influence on the perceived usefulness of AI.
H5: Government policy has a positive influence on the perceived usefulness of AI.
H6: System quality has a positive influence on perceived ease of use of AI.
H7: Service quality has a positive influence on perceived ease of use of AI.
H8: Information quality has a positive influence on perceived ease of use of AI.
H9: Technical support has a positive influence on perceived ease of use of AI.
H10: Government policy has a positive influence on perceived ease of use of AI.
H11: Perceived ease of use has a positive influence on perceived usefulness of AI.
H10: Government policy has a positive influence on perceived ease of use of AI.
H12: Perceived usefulness has a positive influence on perceived trust of AI.
H13: Perceived ease of use has a positive influence on perceived trust of AI.

H14: Perceived trust has a positive influence on the intention to adopt AI among the government servants in the UAE.
H15: Perceived trust moderates the relationship between perceived usefulness and the intention to adopt AI among the government servants in the UAE.
H16: Perceived trust moderates the relationship between perceived ease of and the intention to adopt AI among the government servants in the UAE.
H17: Data privacy concern has a positive influence on perceived ease of use of AI.
H18: AI awareness has a positive influence on perceived ease of use of AI.
H19: Top management support has a positive influence on perceived ease of use of AI.
H20: Industry pressure has a positive influence on perceived ease of use of AI.

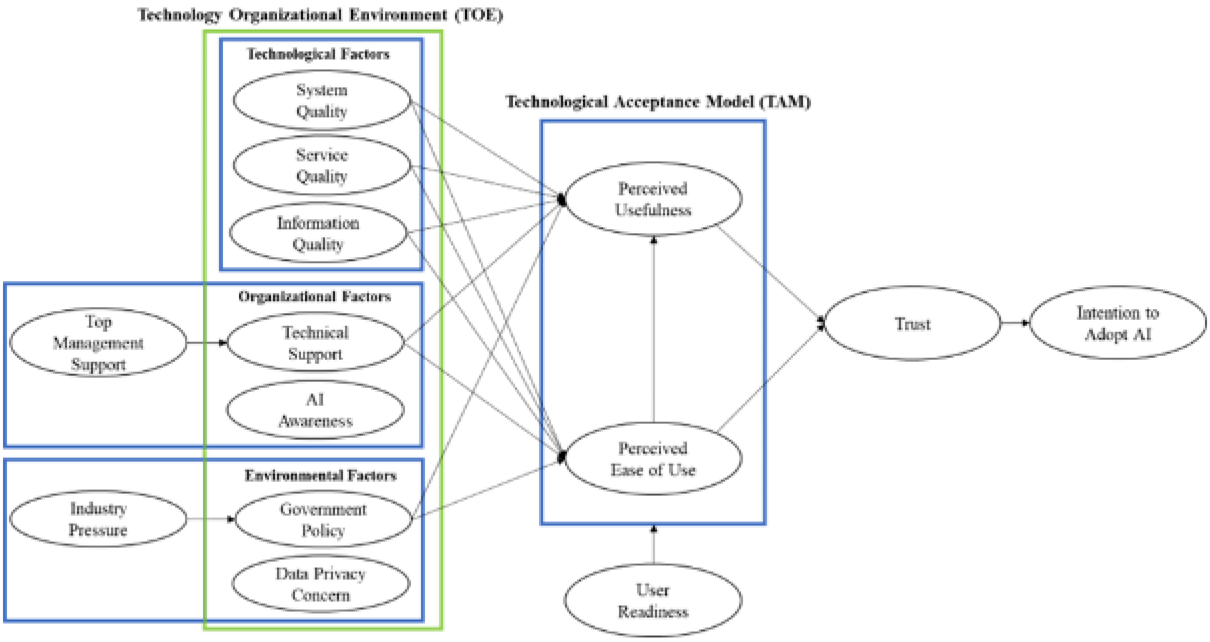

Figure 1: The Research Model Framework

Methodology

Measurement Instruments

The measurement instrument was adapted from prior validated studies to ensure theoretical soundness. Items for system quality, service quality, information quality, and technical support were adapted from Sulaiman et al., (2023); AI awareness from Jöhnk et al., (2021) and Venkatesh et al., (2003); top management support from Premkumar and Roberts (1999) and Ifinedo (2011); government policy from Jais et al., (2024); data privacy concerns from Bansal et al. (2016) and Malhotra et al. (2004); external pressure from Li et al., (2024); perceived ease of use and perceived usefulness from Warkentin et al. (2007); trust from Kang et al., (2024); user readiness from Falebita and Kok (2025); and intention to adopt AI from Chatterjee et al. (2021).

Pre-Test

Prior to pilot testing, the questionnaire underwent a pre-test following the recommendations from Devisakti and Ramayah (2019). The survey questionnaire was emailed to four experts in management and marketing to assess content validity, clarity of wording, and whether the items accurately measured the intended constructs. Feedback from the experts led to minor revisions to enhance clarity and contextual relevance, ensuring that the instrument was appropriate for the UAE government sector.

Pilot Test

Pilot testing is a critical step in survey research, as it allows researchers to identify potential issues with questionnaire wording, item interpretation, and construct measurement before the full-scale study (Hair et al., 2019). This process helps ensure the instrument is both valid and reliable, reducing measurement errors and enhancing the quality of data collected (Sekaran & Bougie, 2016). Internal consistency of all constructs was assessed using Cronbach's alpha, a widely used reliability measure in behavioural research, with values above 0.70 deemed acceptable (Nunnally, 1978; Hair et al., 2020). While there is no strict rule for pilot test sample size, past studies suggest 20-50 respondents are sufficient to evaluate reliability and identify major issues in the instrument without being resource-intensive (van Teijlingen & Hundley, 2001). In this study, pilot test was conducted with 32 UAE government servants using convenience sampling to evaluate the reliability of the instrument.

Correlations

In addition to internal consistency, inter-construct correlations were examined to provide preliminary evidence of convergent and discriminant validity. Correlation analysis helps identify whether items within the same construct are appropriately related, and whether constructs are distinct from one another (Burns & Burns, 2008).

Data Analysis

The combination of Cronbach's alpha and correlation analysis ensures that the instrument is both reliable and valid prior to its deployment in the main study, reducing measurement errors and enhancing the robustness of subsequent structural analyses. Cronbach's alpha and correlation analyses were conducted using the Statistical Package for the Social Sciences (SPSS) version 27.0.

Results

The results indicate that all constructs demonstrated excellent reliability, with alpha values well above the recommended threshold of 0.70, as shown in Table 1.

Among the technology-related constructs, system quality ($\alpha = 0.945$), service quality ($\alpha = 0.942$), information quality ($\alpha = 0.953$), and technical support ($\alpha = 0.970$) showed very high internal consistency, indicating that the items consistently measure the technological support dimensions of AI adoption. For organizational and environmental factors under the TOE framework, top management support ($\alpha = 0.944$), government policy ($\alpha = 0.954$), data privacy concerns ($\alpha = 0.962$), and external pressure ($\alpha = 0.943$) also exhibited strong reliability. Similarly, AI awareness recorded a high reliability coefficient ($\alpha = 0.936$), suggesting consistent measurement of respondents' familiarity with AI.

Regarding TAM-related constructs, perceived ease of use ($\alpha = 0.968$) and perceived usefulness ($\alpha = 0.973$) achieved excellent reliability values. additional user-related constructs, including trust ($\alpha = 0.957$), user readiness ($\alpha = 0.953$), and intention to adopt AI ($\alpha = 0.967$), also demonstrated strong internal consistency.

Overall, the reliability results confirm that the adapted instrument possesses high internal consistency across all constructs, supporting its suitability for use in the main study on AI adoption among UAE government servants.

Table 1
Cronbach's Alpha Results

Construct	No. of Item	Cronbach's Alpha
System Quality	6	0.945
Service Quality	5	0.942
Information Quality	6	0.953
Technique support	7	0.970
AI Awareness or Knowledge	4	0.936
Top Management Support	4	0.944
Government Policy	4	0.954
Data Privacy Concerns	6	0.962
External Pressure	3	0.943
Perceived Ease of Use	7	0.968
Perceived Usefulness	6	0.973
Trust	4	0.957
User Readiness	5	0.953
Intention to Adopt AI	4	0.967

Correlation Results
The correlation analysis was conducted to examine the strength and direction of the relationships between the variables. As presented in Table 2, the results indicate that all variables are positively correlated. The high intercorrelations among the independent variables further indicate internal consistency and reliability of the measurement constructs.

Table 2
Correlation Results

	1	2	3	4	5	6	7	8	9	10
1. AI Intent	1.000									
2. SysQual	.668	1.000								
3. ServQual	.755	.829	1.000							
4. InfoQual	.741	.826	.995	1.000						
5. TechSup	.751	.837	.998	.993	1.000					
6. AI Awr	.760	.805	.982	.983	.980	1.000				
7. TopMS	.755	.829	.995	.995	.992	.988	1.000			
8. GovtPol	.744	.798	.966	.957	.972	.979	.963	1.000		
9. DataPC	.696	.826	.976	.974	.982	.970	.976	.980	1.000	
10. ExtPre	.721	.796	.976	.973	.981	.978	.974	.983	.986	1.000

Discussion and Conclusion
This study presents a preliminary assessment of the constructs used to examine the relevance of the TAM and TOE frameworks in predicting AI adoption intention among UAE government servants. The pilot results indicate that all constructs demonstrated high reliability and satisfactory correlation values, confirming that the measurement model is suitable for testing in the main study.

Theoretically, this study contributes to the growing literature on AI adoption, which is particularly timely given AI's widespread application across both government and private sectors to streamline work processes. Moreover, the study extends the TAM and TOE frameworks by integrating them and incorporating additional constructs, resulting in a more robust and comprehensive model for explaining AI adoption behaviour.

In practice, the findings of this study provide valuable insights for public sector managers and policymakers aiming to accelerate AI adoption within government institutions. As AI becomes increasingly integral across sectors globally, neglecting its implementation could leave government operations behind. Therefore, concerted efforts are needed to strengthen digital infrastructure, enhance technical support, implement supportive regulatory and data protection policies, and foster trust, all of which can encourage AI adoption.

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