

Integrating Task–Technology Fit and AI Transparency to Explain Artificial Intelligence Adoption: The Mediating Role of AI Trust

Sultan Saif Al Maawali^{1*}, Azlina Binti Abdullah², Abbod Altamami³, Wan Noordiana Wan Hanafui⁴

¹ College of Accounting and Business Management, Universiti Tenaga Nasional (UNITEN), Malaysia
Email: almawalisultan@gmail.com

² College of Accounting and Business Management, Universiti Tenaga Nasional (UNITEN), Malaysia
Email: azlina@uniten.edu.my

³ College of Accounting and Business Management, Universiti Tenaga Nasional (UNITEN), Malaysia, Email: abbod.naseb@uniten.edu.my

⁴ UNITEN Business School KSHAS, Muadzam Shah, Pahang, Malaysia, Email: diana.hanafi@uniten.edu.my
Corresponding Author: Sultan SAIF AL MAAWALI

Abstract: The present study aims to explore how AI can be adopted in governmental ministries in Oman by combining the Task–Technology Fit theory with AI Transparency and AI Trust. A structured questionnaire was used in collecting data from 392 employees from Ministry of Justice, Ministry of Transport, Communications and Information Technology and Ministry of Health. Using SmartPLS, the measurement and structural models were assessed by means of Partial Least Squares Structural Equation Modelling (PLS-SEM). The results reveal that Task Characteristics and Technology Characteristics significantly impact Task–Technology Fit, which in turn positively affects AI Trust and AI Adoption, and AI Transparency positively influences AI Trust and AI Adoption. AI Trust also plays an important role in AI Adoption and serves as a mediator between Task–Technology Fit and AI Transparency and AI Adoption. Task–Technology Fit was accounted for by the model to the extent of 51.7%, AI Trust to the extent of 40.1% and AI Adoption to the extent of 41.8%. These findings highlight the importance of functional alignment, transparently managed systems, and employee trust, providing practical insights for implementing and governing AI in the public sector. The results support all seven direct and two mediation hypotheses proposed.

Keywords: AI Adoption, Task–Technology Fit, AI Transparency, AI Trust, Omani Governmental Ministries, PLS-SEM

1. Introduction

AI has emerged as an important component of public-sector digital transformation, supporting administrative automation, large-scale data processing, predictive analysis, policy decision-making, risk identification, and service delivery. The implementation of AI in government is influenced by various technical, organisational, environmental, and user factors, though From a technological perspective, AI systems are more likely to be embraced when they can be integrated with current procedures, are user friendly, can be configured to align with the employees' tasks, and can show clear benefits over traditional practices (Horani et al., 2025; Khalil & Al-Ali, 2026; Russo, 2024). While AI offers the potential for quick data processing, predictive analytics, and intelligent decision-making, its implementation can be hindered by various factors, such as insufficient infrastructure, lack of technical expertise, and integration challenges with existing systems (Maragno et al., 2023).



The readiness of the organisations is also essential. Senior-management commitment is a key enabler for the adoption of AI as it involves allocating resources, first setting the direction and then coordinating its implementation, as well as instilling employee engagement with AI-enabled practices (Horani et al., 2025; Ren Kon et al., 2026). Public organisations also have to decide if the capabilities of AI are brought together in dedicated data-science teams or if they are spread over business units, as this will impact coordination and accountability as well as process alignment (Selten & Klievink, 2024). The readiness of employees is also a factor in implementation, as a lack of knowledge of AI or insufficient digital skills can lead to lack of confidence and effective use. To this end, targeted training and ongoing capability development programmes are needed to enhance workforce competence to facilitate responsible use (Smith et al., 2025).

In addition to the internal factors, external and institutional conditions influence government AI adoption. Innovative supportive regulatory frameworks can induce innovation, and cross-sector collaboration can provide a means of institutional capacity-building and knowledge sharing in uncertain technological contexts (Mikhaylov et al., 2018). On the other hand, worries about data privacy, algorithmic bias, transparency, accountability and ethical responsibilities may be unfavorable to implementation or limit public legitimacy. Acceptance can also be influenced by social factors and the belief that AI will enhance service quality and cut down on administrative inefficiencies (Johnson, 2026). These determinants are not uniform but vary across national and sectoral contexts, highlighting the need to tailor AI-adoption strategies to institutional conditions, workforce characteristics, and specific public-service requirements (Mercuri et al., 2025).

Task–Technology Fit (TTF) theory provides a framework for understanding the extent to which the capabilities of AI applications align with employees’ task requirements. The theory suggests that the adoption of technology and performance is contingent on task–technology fit. Task characteristics encompass complexity, variability, intensity of information processing, interdependence, and amount of judgement. Technology characteristics include usefulness, ease of access, reliability, speed, precision and responsiveness. Task–technology fit occurs when these capabilities allow users to execute their tasks effectively and generate better results (Cane & McCarthy, 2009; Goodhue & Thompson, 1995).

This alignment is of utmost significance in AI-assisted work. AI is used by the Government for data interpretation, forecasting, risk detection, document processing and decision support. However, a complex AI system can still be underutilised if the user's job doesn't match the capabilities of the AI system. Automation tools that are primarily created for day-to-day tasks might not be appropriate for tasks that involve professional judgment, and sophisticated analytical systems might not prove valuable in straightforward and standardized processes (Parsons et al., 2025). Empirical evidence suggests that good task–technology fit is more likely to enhance individual and team performance, but poor fit can lead to reduced perceived usefulness and less likelihood of continued use. Combining Task–Technology Fit theory with a wider acceptance perspectives can therefore offer a more comprehensive explanation for how functional compatibility influences perceptions, behavioral intentions, and technology mediated outcomes (Chavarnakul et al., 2024).

However, task–technology fit by itself may not be enough to account for employee willingness to adopt AI. Even if an application can be used for relevant activities, users may be reluctant to trust its results, due to the lack of visibility of the data, reasoning processes, and operational restrictions involved in the application (Akben & Dong, 2025). AI transparency offers a valuable complementary view that allows users to gain a better understanding of the operations and rationale behind specific recommendations made by the system. Transparency can include providing information regarding the data leveraged, criteria for making decisions, accuracy, limitations of use, and ways for human oversight (Kaplan et al., 2024; Yu et al., 2023).

Transparent AI can minimize uncertainties by giving users the ability to determine whether system recommendations are logical, accurate, and fit the context of the decision. It can also help improve accountability and fairness by adding transparency to the information processing, what drives the outputs, who can review and/or correct errors, etc. Explanations of the system behaviour that are understandable to users and lessen the uncertainty about

black-box decisions are generally more likely to encourage users to rely on AI (von Eschenbach, 2021). It is especially crucial in government institutions that transparency is paramount, ensuring that decisions made with AI are accountable, defensible, and procedurally legitimate. Appropriate explanations can help to make automated decisions seem more legitimate than full disclosure of a complex algorithm (Fine Licht & Fine Licht, 2020).

However, increased transparency is not necessarily a boost to acceptance. Overly technical or detailed explanations can cause a cognitive overload and heighten evaluation and lower confidence. Transparency should thus be adapted to the user's knowledge and skills, the complexity of the task and the decision context (Ngo, 2025). Good transparency is not just the amount of information that is made available, but the explanations that are understandable, relevant, and actionable.

AI trust is the users' confidence in relying on a system that is viewed as capable, reliable, predictable, and acceptable. Trust is critical when an employee isn't able to see complex algorithmic processes. Explainable AI can help to build trust by providing reasons for recommendations that are easy-to-understand, but this can hinge on system performance, perceived risk, and the quality of the explanation (De Brito Duarte et al., 2023). Trust can also be influenced by transparency factors like correctness, clarity, and proper disclosure, especially when they add to the usefulness and functionality of the system (Lee & Cha, 2025). Consistent reliable performance of AI systems with clear reasoning helps users adopt and use them in everyday tasks and for ongoing organisational use (Wanner et al., 2022).

Although there is research on task–technology fit, transparency, trust, and AI adoption, these areas are typically studied individually. Task–Technology Fit research addresses the fit of technological capabilities and work requirements, while AI, governance research addresses explainability, accountability, safeguards and public trust. Trust has been often modelled as a direct predictor in technology-adoption models which provides little understanding of how functional alignment and transparent system behaviour can jointly support technology-adoption. The study aims to fill this gap by combining the Task–Technology Fit theory with AI transparency and AI trust to account for AI adoption within Omani governmental ministries. It examines the influence of task and technology characteristics on fit, fit on trust, fit on adoption and if trust is a mediator for these relationships. This framework builds on the Task–Technology Fit theory and offers practical suggestions for implementing AI in the public sector.

2. Literature Review

2.1 AI Adoption in Governmental Organisations

The adoption of artificial intelligence (AI) is the continuous integration of AI-powered systems into the tasks, decisions, and organisational processes of employees. In governmental institutions it goes beyond first-time experiment to sustained use, reliance on AI-generated outputs, and embedding of AI products in governmental administrative, analytical, and professional processes. AI adoption will be more likely when employees find AI helpful, easy to use, compatible with their workflow, and better than traditional approaches (Alkaabi et al., 2026; Mercuri et al., 2025). But there is a need for organisational support as well. Leaders' support, sufficient resources, clear structures of implementation, and supportive policies facilitate staff's readiness, while a lack of guidance can contribute to resistance (Khalil & Al-Ali, 2026). Views on privacy, job loss, self-determination and control also play a role in adoption. Confidence and acceptance can be enhanced by training, organisational culture and technical support (Dabbous et al., 2022).

2.2 Task–Technology Fit Theory

Task–Technology Fit explains the use of technology by the alignment of the capabilities of the system and the user's task requirements. The framework consists of task characteristics, technology characteristics, and task–technology fit. Task characteristics are complexity, information requirements, interdependence and regulatory obligation, while technology characteristics are functionality, reliability, analytical ability, accessibility and decision-support capability (Cane & McCarthy, 2009; Goodhue & Thompson, 1995). Fit is achieved when these abilities

enhance the performance of assigned roles, leading to utilisation, better performance and higher perceived value of technology. The healthcare systems as well as mobile information systems demonstrate that a system put together by design, can address the demands of operation better and therefore create a better outcome (Chen et al., 2015). This is especially true for governmental AI when departments are responsible for various administrative, analytical, regulatory and policy functions. It is crucial, therefore, to assess task requirements before the rollout of AI in government organisations (Aslam et al., 2025).

2.3 Task Characteristics and Task–Technology Fit

Task characteristics refer to the structural or cognitive demands of the work tasks of employees, such as complexity, variability, interdependence, information-processing requirements, time demands, and professional judgement. These needs span various areas of government, including routine administrative tasks to sophisticated regulatory and policy decisions. Uncertainty, multiple goals and extensive reasoning are tasks that demand higher-level technological assistance than routine tasks (Campbell, 1988). This is influenced by whether AI capabilities align with the tasks' requirements. Some tasks can be automated and standardized, while others are complex and need to be interpreted in context, analytically flexible and monitored by humans. AI systems must also facilitate coordination between different departments for interdependent tasks (Agrawal et al., 2024). Perceived fit is additionally determined by information-intensive work, as when employees process large data sets or conditions, as suggested by Allegrini et al. (2022). Hence, it is important to have a clear classification of tasks to enable the appropriate deployment of AI (Fernández-Macías & Bisello, 2022).

H1. Task Characteristics positively and significantly influence Task–Technology Fit in Omani governmental ministries.

2.4 Technology Characteristics and Task–Technology Fit

Technology characteristics are attributes of the AI system that can enable or constrain how employees work, such as the analytical capability, accuracy, reliability, responsiveness, accessibility, interface quality, security, processing speed and availability. They can be as useful as the task they are used for as well as the technical sophistication. The match between AI abilities and user actions can facilitate users' perception that the system is useful and their effective use of it (Wang et al., 2026). Effective AI can enhance the task–technology fit by offering the necessary information and recommendations in time, explaining the process clearly and consistently and perform the task reliably, which, in turn, can increase productivity, satisfaction, and engagement (Marikyan et al., 2022). On the other hand, unpredictable output, limited contextual awareness, laggy responses and complicated interfaces could decrease fit. Hence, effective design should strive to encourage human–AI collaboration by making them transparent, user-controllable, accountable, and user-centred in delivering information (Blaurock et al., 2024; Lv et al., 2026).

H2. Technology Characteristics positively and significantly influence Task–Technology Fit in Omani governmental ministries.

2.5 Task–Technology Fit and AI Trust

Task–Technology Fit refers to the degree of match between the capabilities of AI and employees' work needs, and how well AI helps them complete their tasks. The consistent delivery of relevant, accurate, and timely outputs by AI gives the user real-world proof of system capabilities. This is crucial, as many AI processes are not directly observable, and employees determine trustworthiness based on performance and task relevance (Cane & McCarthy, 2009; Goodhue & Thompson, 1995). People's perception of the ability, reliability, and predictability of AI is the basis for building trust. Better consistency indicates reliability of the system and will more likely be seen as reliable and used for regular work (Choung et al., 2023). On the other hand, if the fit is bad, outputs that are irrelevant, duplication, inconsistencies, and extra verification can be generated, which can lead to a decline in confidence. Task–technology fit thus indicates a performance value and trustworthiness of AI (Regona et al., 2026).

H3. Task–Technology Fit positively and significantly influences AI Trust in Omani governmental ministries.

2.6 Task–Technology Fit and AI Adoption

One of the basic assumptions of Task–Technology Fit theory is that users will be more likely to use technologies whose capabilities match their work demands. Strong fit in AI environments leads to employees feeling systems are relevant, useful, and supportive as opposed to being imposed on them. With AI support in analysis, coordination, optimisation or information processing, users can be more efficient and generate better results. A good fit also increases satisfaction, perceived usefulness, and use. In supply-chain scenarios, findings reveal that both generative AI and task alignment are associated with increased trust and satisfaction, while technology anxiety can have a negative impact on these outcomes (Aslam et al., 2025). The results align with those in the field of higher education, where the responsible use of AI tools is fostered by well-matched tools (Wang et al., 2026). On the other hand, a poor fit will lead to duplication, error, and manual work, which will decrease utilisations and continuance intention (Zhang et al., 2025).

H4. Task–Technology Fit positively and significantly influences AI Adoption in Omani governmental ministries.

2.7 AI Trust and AI Adoption

AI Trust is the user's belief that an AI system can do the job, is reliable, predictable, and is ethically acceptable. It is particularly relevant when employees are not able to review algorithmic processes, or check each and every output individually. Trust requires technical attributes like precision, security, durability, and dependability, along with fairness, legality, privacy, and responsibility (Afroogh et al., 2024). Employees who trust AI are more likely to take action based on AI suggestions, integrate AI-generated content into their tasks, and use AI to make data-driven, time-sensitive decisions. Functionality-based trust is especially powerful, as users judge the system's reliability based on its performance in consistently completing tasks and helping them accomplish their own work (Choung et al., 2023). It is crucial, therefore, that government institutions build trust through explainability, accountability, stakeholder engagement, institutions safeguards, and some metrics of trustworthy AI (Robles & Mallinson, 2025).

H5. AI Trust positively and significantly influences AI Adoption in Omani governmental ministries.

2.8 AI Transparency and AI Trust

AI Transparency is a measure of the users' understanding of how the AI system works, how it uses data, how it produces outputs, and how it communicates its limitations. It can be supported with explanations, documentation, disclosure of criteria for making a decision, communication of uncertainty, and the identification of the human responsibility. Transparency helps users to evaluate the suitability of the AI's recommendations and align them with the organisation's needs (Schmidt et al., 2020). Transparent AI can enhance the legitimacy in public administration, as employees and citizens are likely to accept decisions better if they understand the role of AI in the decision-making process (Fine Licht & Fine Licht, 2020). But too much tech disclosure can be overwhelming and undermine confidence. There is therefore a need to balance transparency with users' expertise, complexity of the task, and informational needs (Ngo, 2025). Contestability, human review and accountability can help enable responsible reliance where interpretability is an impractical approach (Lee & Cha, 2025).

H6. AI Transparency positively and significantly influences AI Trust in Omani governmental ministries.

2.9 AI Transparency and AI Adoption

Transparency can directly facilitate the adoption of AI, by assisting employees in understanding, assessing and justifying the recommendations proposed by the system. Clear explanations gives users more control and allows employees to decide if outputs are suitable for specific tasks, which decrease uncertainty and contribute to employee's use of the technology on a more regular (Wanner et al., 2022). Especially in governmental organisations, where

decisions need to be justified to supervisors, regulators, staff and citizens. Opaque systems can lead to resistance as users will be unable to show compliance with administrative and ethical needs, or see recommendations. In contrast, there are a range of factors that can help enhance legitimacy and organisational integration, through meaningful explanations and clear accountability mechanisms (Fine Licht & Fine Licht, 2020). But this may cause more cognitive load and less acceptance of too much technical detail. Transparency should thus be based on the users' expertise and complexity of the task (Ngo, 2025). User-centred explainability can foster usability, perceived control, decision validation and adoption (Kaplan et al., 2024).

H7. AI Transparency positively and significantly influences AI Adoption in Omani governmental ministries.

2.10 Mediating Role of AI Trust

The proposed framework places AI Trust as a mechanism through which Task–Technology Fit and AI Transparency impact AI Adoption. Task–Technology Fit can directly facilitate the adoption when the AI capability is aligned to the work needs of employees, and when it enhances the efficiency, accuracy, or quality of their decisions. It can also work indirectly, implying technological expertise. Employees will trust and feel the system is reliable when it repeatedly delivers reliable supports and that the employees will use the output of the system (Arora & Mittal, 2025; Salwin et al., 2026).

H8. AI Trust mediates the positive relationship between Task–Technology Fit and AI Adoption in Omani governmental ministries.

AI Transparency could also bolster adoption by minimizing uncertainty about how the system processes data, how it uses it, and how it arrives at decisions. Clear explanations enable staff to think about recommendations and build confidence in the technology, which leads to their increased willingness to use it (Wanner et al., 2022). There are more chances to develop the right kind of trust with adaptive transparency, taking into account user expertise and task complexity, than with the unrestricted disclosure of technology (Ngo, 2025). Thus, AI Trust translates functional alignment and comprehensible system behaviour into trust, reliance and ongoing adoption.

H9. AI Trust mediates the positive relationship between AI Transparency and AI Adoption in Omani governmental ministries.

2.11 Research Gap

While research on AI-adoption has explored perceived usefulness, organisational culture, technology anxiety, job insecurity, and employee self-image (Dabbous et al., 2022), there is a lack of research on functional alignment, transparency, and trust. Previous research has shown that the alignment between AI capabilities and task requirements, known as Task–Technology Fit, positively increases trust, satisfaction, perceived usefulness, responsible use, and adoption (Aslam et al., 2025; Wang et al., 2026). Explainability, accountability, reliability, and understandable communication are further key factors that contribute to acceptance and trust in transparency research (Regona et al., 2026; Yang et al., 2026). But such views are not sufficiently mainstreamed in government. This study aims to bridge the gap by analyzing the causal relationships between Task–Technology Fit, AI Trust, and AI Adoption within the context of Omani governmental ministries, considering the influence of task and technology attributes on Task–Technology Fit and the role of Task–Technology Fit and transparency in shaping AI Trust, which in turn impacts AI Adoption.

3. Conceptual Frameworks

The conceptual framework as shown in Figure 1 is based on the combination of Task–Technology Fit theory and AI Transparency and AI Trust for explaining the AI Adoption in the governmental ministries in Omani. Task Characteristics and Technology Characteristics are identified as the antecedents to Task–Technology Fit, which is hypothesized to directly affect AI Adoption as well as indirectly via AI Trust. AI Transparency is also envisioned as

having an impact on both AI Trust and AI Adoption, which in turn directly impacts adoption. It posits that AI acceptance does not only rely on the technical aspects, as employees' perceptions of task alignment, system interpretability and technological reliability play a crucial role in this process. Task–Technology Fit encapsulates functional suitability, AI Transparency denotes openness and explainability, and AI Trust embraces the confidence mechanism that connects these perceptions to adoption. Based on this, seven direct links and two mediation pathways are proposed, which integrates to explain the sustained use of AI in governmental work.

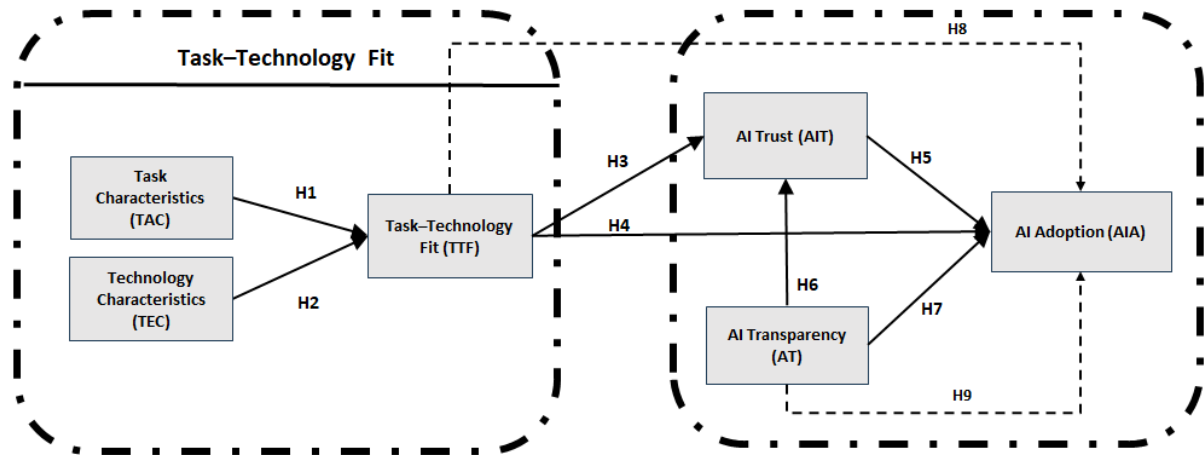


Figure 1. Conceptual framework of the study.

4. Methodology

This study aimed to investigate the association between Task Characteristics, Technology Characteristics, Task–Technology Fit, AI Transparency, AI Trust and AI Adoption in selected governmental ministries in Oman. The study used a quantitative, deductive, explanatory and cross sectional research design. Seven direct relationships and two mediating effects were tested using nine hypotheses. The information obtained was from a structured self-administered questionnaire sent to managerial staff working in the ministries selected. The resultant data was analysed by employing PLS-SEM with the SmartPLS software, which helps to test measurement reliability, construct validity, structural relationships and the mediation effect of AI Trust.

4.1 Research Instruments

The research instrument consisted of 10 reflective constructs with items adapted from existing studies and connotated for AI usage in governmental organisations in Oman. Task Characteristics evaluated the work complexity, information integration, coordination, variability, and interpretive demand (Goodhue & Thompson, 1995). Technology Characteristics observed the interface clarity, navigation, accuracy, responsiveness, reliability, and system availability (Park, 2019; Ulfa et al., 2024). Task–Technology Fit quantified the match between the capabilities of AI and employees' task requirements, procedures, efficiency and quality expectations (Goodhue & Thompson, 1995; Zhou, 2012).

AI Trust assessed perceived reliability, competence, impartiality, comfort and tendency to rely on AI-supported decisions (Kalyar et al., 2013; McGrath et al., 2025; Sun et al., 2025). AI Transparency evaluated understanding, explainability, information disclosure, predictability as well as anticipated system responses (Angelopoulos et al., 2025), while AI Adoption assessed the current use, future intention, frequency, reliance, and integration of AI into the workplace (Zeng et al., 2022). A five-point Likert scale varying from strongly disagree to strongly agree was used for all the items (Al-Zubaidi et al., 2022).

4.2 Sampling and Data Collection

The target population consisted of around 10,450 employees working in three Omani ministries, namely: Ministry of Justice, the Ministry of Transport, Communications and Information Technology and the Ministry of Health. Stratified convenience sampling provided the representation at ministries, departments. The minimum sample calculated at 5% margin of error, 50% population proportion and 95% confidence level (Raosoft) was 371. A total of 522 surveys were electronically distributed and 401 returned, 392 of which were deemed to have valid data and no screening for missing responses, straight lining, incompleteness and/or invalid patterns. Coding, demographic analysis, outlier detection and preliminary screening were conducted using SPSS. SmartPLS calculated loadings, Cronbach's alpha, composite reliability, rho_A, AVE, HTMT, VIF, path coefficients, R2, f2 and Q2. Direct and mediated relationships were tested with 5,000 resamples using bootstrapping.

5. Results

5.1 Respondents Profile

The demographic profile in Table 1 presents a summary of 392 employees from three Omani ministries, who were broadly represented in both occupational and departmental categories as well as in terms of experience. The male respondents were 62.5% and the female respondents were 37.5%.

Respondents'	Category	Frequency	Percentage
Gender	Male	245	62.50%
	Female	147	37.50%
Age	Below 25	63	16.07%
	30-39	132	33.67%
	40-49	166	42.35%
	Above 50	31	7.91%
	Diploma	54	13.78%
Education Level	Bachelor's Degree	202	51.53%
	Master's Degree	85	21.68%
	PhD	44	11.22%
	Others	7	1.79%
	Administrative / Support Staff	154	39.29%
Position	Technical / Engineering Staff	115	29.34%
	Professional officer / specialist	42	10.71%
	Supervisory Level	65	16.58%
	Middle Management	14	3.57%
Department	IT / Digital Transformation	87	22.19%

Respondents'	Category	Frequency	Percentage
Experience Years	Operations / Service Delivery	84	21.43%
	Planning / Strategy	44	11.22%
	HR / Administration / Finance	53	13.52%
	Legal / Policy / Regulatory	68	17.35%
	Medical / Clinical / Health systems	44	11.22%
	Other	12	3.06%
	Less than 5 years	49	12.50%
	5–10 years	65	16.58%
	11–15 years	76	19.39%
	16–20 years	139	35.46%
Ministry	More than 20 years	63	16.07%
	Ministry of Justice	148	37.76%
	Ministry of Transport, Communications and Information Technology	135	34.44%
	Ministry of Health	109	27.81%

Table 1. Respondents' profile

The largest age group was 40–49 years (42.35%), followed by 30–39 years (33.67%). Majority of the participants (51.53%) had a bachelor's degree while 21.68% had a master's degree and 11.22% had a PhD. Administrative/support staff were the biggest occupational group (39.29%) followed by technical/engineering staff (29.34%). The respondents were primarily from IT/digital transformation (22.19%) and operations/service delivery (21.43%). Over half were experienced with more than 15 years of experience. Justice had 37.76%, Transport, Communications and Information Technology 34.44% and Health 27.81% representation. This distribution aids secure research throughout institutional and professional settings explored.

5.2 Validity of the Measurement Model

The measurement model was assessed prior to evaluating the structural model. The six constructs were examined for indicator reliability, internal consistency reliability, convergent validity, and discriminant validity in accordance with PLS-SEM guidelines. Indicator reliability was assessed using outer loadings, internal consistency reliability using Cronbach's alpha and composite reliability (CR), convergent validity using average variance extracted (AVE), and discriminant validity using the heterotrait–monotrait ratio (HTMT) (Hair et al., 2019). Descriptive statistics, including the mean and standard deviation, were also reported for each indicator.

5.3 Convergent Validity

Outer loadings, Cronbach's alpha, composite reliability, and average variance extracted were used to evaluate convergent validity. All loadings were above the recommended value of 0.708 (Shmueli et al., 2019), which ranged from 0.836 to 0.868 indicating good indicator reliability. Task Characteristics recorded $\alpha = 0.922$, CR = 0.939, and AVE = 0.718, while Technology Characteristics achieved $\alpha = 0.910$, CR = 0.933, and AVE = 0.735. Task–Technology Fit produced $\alpha = 0.924$, CR = 0.940, and AVE = 0.723. AI Trust reported $\alpha = 0.924$, CR = 0.941, and AVE = 0.726. AI Transparency showed the strongest values, with $\alpha = 0.928$, CR = 0.944, and AVE = 0.736. AI Adoption recorded $\alpha = 0.923$, CR = 0.940, and AVE = 0.722. Overall, all constructs' reliability and validity exceeded accepted norms, and the constructs were found to have adequate convergent validity and were used in the subsequent structural model assessment and hypothesis testing.

5.4 Discriminant Validity

Heterotrait–monotrait ratio was used to determine the discriminant validity. As seen in table 3, the HTMT values was between 0.184 and 0.675 which was less than the conservative value of 0.85 (Al-Zubaidi et al., 2023; Hair et al., 2019) It was found that the highest value is between Technology Characteristics and Task–Technology Fit (0.675), Task Characteristics and Task–Technology Fit (0.621). The results indicate that all six constructs have been empirically distinct and the measurement model is appropriate for further structural analysis. Therefore, no problem conceptual overlap was found between the variables examined.

Construct and items	Code	Mean	Std. Deviation	Loading	Cronbach's alpha	CR	AVE
Task Characteristics							
1. My tasks require me to gather information from different sources.	TAC1	3.4541	0.80468	0.848	0.922	0.939	0.718
2. My tasks require me to integrate information from multiple sources to make decisions.	TAC2	3.4847	0.83084	0.842			
3. My tasks often involve solving problems without clear steps or procedures.	TAC3	3.4796	0.83073	0.846			
4. My tasks require working closely with others to complete them.	TAC4	3.5128	0.80589	0.837			
5. My tasks change depending on new situations or requirements.	TAC5	3.5255	0.80558	0.849			
6. My tasks require me to understand and interpret complex information.	TAC6	3.5306	0.82733	0.862			
Technology Characteristics							
1. The AI system interface is clear and easy to understand.	TEC1	3.5128	0.78986	0.855	0.91	0.933	0.735
3. The AI system provides accurate information when I use it.	TEC3	3.4617	0.83318	0.856			
4. The AI system responds quickly when I use it.	TEC4	3.4796	0.81520	0.849			
5. The AI system operates reliably without errors or interruptions.	TEC5	3.4974	0.82170	0.859			
6. The AI system is available whenever I need to use it.	TEC6	3.4209	0.83948	0.867			
Task–Technology Fit							
1. The system matches the requirements of my work tasks.	TTF1	3.4668	0.83340	0.845	0.924	0.940	0.723
2. The system supports me in completing my tasks efficiently.	TTF2	3.4566	0.81743	0.858			
3. The system fits well with the quality requirements of my tasks.	TTF3	3.4413	0.80702	0.838			
4. The system supports the way I usually perform my tasks.	TTF4	3.4311	0.83427	0.867			
5. The system has the capabilities needed to handle my job tasks.	TTF5	3.4847	0.81844	0.859			
6. The system provides the right tools and functions to carry out my tasks.	TTF6	3.4439	0.81978	0.836			
AI Trust							
1. I trust the AI system when it performs my work tasks.	AIT1	3.5077	0.83095	0.847	0.924	0.941	0.726
2. The AI system performs its functions reliably.	AIT2	3.4949	0.85224	0.844			
3. I believe the AI system provides honest and unbiased outputs.	AIT3	3.5179	0.87575	0.857			
4. I feel comfortable relying on the AI system during my work.	AIT4	3.5587	0.86514	0.850			
5. The AI system has the ability to perform tasks effectively.	AIT5	3.5128	0.85216	0.861			
6. I am willing to rely on the AI system for important work decisions	AIT6	3.4821	0.83693	0.852			
AI Transparency							
1. I clearly understand what the AI system does.	AT1	3.4770	0.83374	0.868	0.928	0.944	0.736
2. The AI system explains how it produces its results.	AT2	3.4949	0.87006	0.857			
3. The AI system shows how it is working during use.	AT3	3.5153	0.81844	0.848			
4. The AI system provides enough information about its actions.	AT4	3.5230	0.83680	0.856			
5. The behavior of the AI system is predictable.	AT5	3.5000	0.86418	0.862			
6. I can anticipate how the AI system will respond to my inputs.	AT6	3.5255	0.82441	0.856			
AI Adoption							
1. I use AI-based systems in my work tasks.	AIA1	3.5638	0.80663	0.840	0.923	0.940	0.722
2. I intend to increase my use of AI systems in the future.	AIA2	3.5026	0.85823	0.862			
3. I use AI systems frequently in my daily work.	AIA3	3.5128	0.80271	0.842			
4. I rely on AI systems to support my work tasks.	AIA4	3.5281	0.86372	0.849			
5. I am willing to adopt AI systems whenever they are available in my work.	AIA5	3.5230	0.83067	0.841			
6. AI systems are integrated into the way I perform my job.	AIA6	3.5051	0.82168	0.863			

Table 2. Construct, Items, Validity and Reliability.

Note: AIA: AI Adoption, AIT: AI Trust, AT: AI Transparency, TAC: Task Characteristics, TEC: Technology Characteristics, TTF: Task–Technology Fit.

	AIA	AIT	AT	TAC	TEC	TTF
AIA						
AIT	0.565					
AT	0.526	0.54				
TAC	0.387	0.249	0.199			
TEC	0.473	0.382	0.232	0.407		
TTF	0.515	0.509	0.184	0.621	0.675	

Table 3. Discriminant validity: Heterotrait-Monotrait ratio (HTMT).

5.5 Assessment of the Structural Model

The structural model was assessed to examine the hypothesised relationships among Task Characteristics, Technology Characteristics, Task–Technology Fit, AI Transparency, AI Trust, and AI Adoption. The assessment included the significance and relevance of the path coefficients, coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2), and model fit, in accordance with established PLS-SEM guidelines (Hair et al., 2019).

Technology Characteristics was shown in Table 4 to be the most influential upon Task–Technology Fit, with an effect size (f^2) of 0.396, which was considered a large effect. Task Characteristics also significantly contributed to Task–Technology Fit ($f^2=0.284$) which is considered medium. AI Transparency showed a medium-sized effect on AI Trust ($f^2=0.306$) and Task–Technology Fit also showed a medium-sized effect on AI Trust ($f^2=0.256$). The impact of AI Transparency ($f^2=0.140$) and Task–Technology Fit ($f^2=0.138$) on AI Adoption was small, as was the effect of AI Trust on AI Adoption ($f^2=0.044$) (Chin, 2010; Cohen, 2013). These results indicate that technological suitability and transparency have a strong impact on fit and trust, while adoption is achieved via a number of parallel processes.

Variable	Values	Rating
AI Trust -> AI Adoption	0.044	Small
AI Transparency -> AI Adoption	0.140	Small
AI Transparency -> AI Trust	0.306	Medium
Task Characteristics -> Task–Technology Fit	0.284	Medium
Technology Characteristics-> Task–Technology Fit	0.396	Large
Task–Technology Fit -> AI Adoption	0.138	Small
Task–Technology Fit -> AI Trust	0.256	Medium

Table 4. Effect Size of predictive Variables

Stone–Geisser's Q^2 was used to determine the predictive relevance.

. All endogenous constructs had values greater than zero indicating the predictive relevance of the model (Hair et al., 2014). As shown in Table 5, the highest predictive power was in Task–Technology Fit ($Q^2=0.514$), followed by AI Adoption ($Q^2=0.363$) and AI Trust ($Q^2=0.302$). Task–technology fit, AI adoption, and AI trust had RMSE values of 0.701, 0.804, and 0.841 and MAE values of 0.555, 0.639, and 0.664, respectively, which were also acceptable (Al-Zubaidi et al., 2025).

Variables	RMSE	MAE	Q^2 (=1-SSE/SSO)
-----------	------	-----	--------------------

AI Adoption	0.804	0.639	0.363
AI Trust	0.841	0.664	0.302
Task–Technology Fit	0.701	0.555	0.514

Table 5. Construct Cross validated Redundancy

Model fit was satisfactory, as shown in Table 6, the SRMR values for the saturated and estimated models were 0.037 and 0.043, both below the recommended threshold of 0.08 (Bentler & Hu, 1998). The corresponding dULS values were 0.841 and 1.144.

Index	Saturated Model	Estimated Model
SRMR	0.037	0.043
d_ULS	0.841	1.144

Table 6. Model fit summary

The results of hypothesis testing showed that all nine hypotheses were supported. Task Characteristics ($\beta=0.398$) and Technology Characteristics ($\beta=0.470$) had a significant impact on Task–Technology Fit. Task–Technology Fit had a positive impact on AI Trust ($\beta=0.397$) and AI Adoption ($\beta=0.321$), and AI Trust significantly affected AI Adoption ($\beta=0.207$). AI Transparency had a positive impact on AI Trust ($\beta=0.433$) and AI Adoption ($\beta=0.329$). Complementary mediation was also found in the case of indirect effect on Task–Technology Fit ($\beta=0.082$) and AI Transparency ($\beta=0.090$).

6. Discussion

The results offer a solid empirical justification for the proposed framework of AI Adoption in Omani governmental ministries. The model validates that it is not one technological property alone that dictates whether or not a person adopts a technology, but task demands, system capabilities, transparency and trust. The variance in Task–Technology Fit was accounted for by Task Characteristics and Technology Characteristics (51.7%) and the variance in AI Trust was accounted for by Task–Technology Fit and AI Transparency (40.1%). Moreover, 41.8% of the variance in AI Adoption was explained by the combination of Task–Technology Fit, AI Transparency and AI Trust. These findings suggest that the framework encompasses both the functional and psychological aspects of employee acceptance of AI.

Hypothesis 1 was accepted, Task Characteristics had a positive and significant impact on Task–Technology Fit ($\beta=0.398$, $t=10.178$, $p<0.001$). The implication from this finding is the consideration of AI's applicability based on the complexity, variability, information intensity, interdependence, and judgement needs of employees' work. More complex technological support is needed for tasks that involve multiple information sources or uncertainty, or that involve coordination between departments, than for standardised tasks. This aligns with the studies by Agrawal et al. (2024); Allegrini et al. (2022); Campbell (1988), who highlighted the significance of task complexity, coordination, and information processing demands. It also reinforces the claim that when tasks are well classified it is possible for organisations to recognise where AI can best augment human capabilities (Fernández-Macías & Bisello, 2022).

Technology Characteristics had the highest influence on Task–Technology Fit ($\beta=0.470$, $t=12.460$, $p<0.001$) and Hypothesis 2 was also supported. The result shows that employees' perception of fit is important to them in terms of accuracy, reliability, responsiveness, accessibility, interface quality, and system availability. This is consistent with the findings of Wang et al. (2026), who suggested that the AI capabilities are worth when they align with the user's actual activities. Additionally, it supports (Blaurock et al., 2024; Lv et al., 2026; Marikyan et al., 2022), who pointed out the significance of consistent performances, user-centred design, transparency, and control. Similarly, advanced functionality doesn't matter if the system is too complicated to use, unreliable, or not a good fit for the operation.

Hypothesis 3 was supported as Task–Technology Fit positively affected AI Trust ($\beta=0.397$, $t=11.120$, $p<0.001$). It builds upon the traditional Task–Technology Fit theory and demonstrates that functional alignment is not only a

factor influencing performance and utilisation but also boosting confidence in AI. Employee gets observable evidence of competence and dependability when systems consistently support, with relevance, accuracy and timeliness. This finding is in line with the work of (Cane & McCarthy, 2009; Choung et al., 2023; Goodhue & Thompson, 1995; Regona et al., 2026), which associates the formation of trust with system performance and relevance of the task.

Hypothesis 4 was accepted, with Task–Technology Fit directly and positively impacting on the AI Adoption ($\beta=0.321, t=7.130, p<0.001$). When AI aligned with their processes and enhanced efficiency, employees were more inclined to embrace the technology. This finding corroborates with (Aslam et al., 2025; Wang et al., 2026; Zhang et al., 2025) results which showed that high alignment positively influences usefulness, satisfaction with the service, responsible usage and continuance intentions. The research also suggests that formal implementation isn't enough to guarantee adoption; AI needs to be useful, in the context of employees' daily tasks.

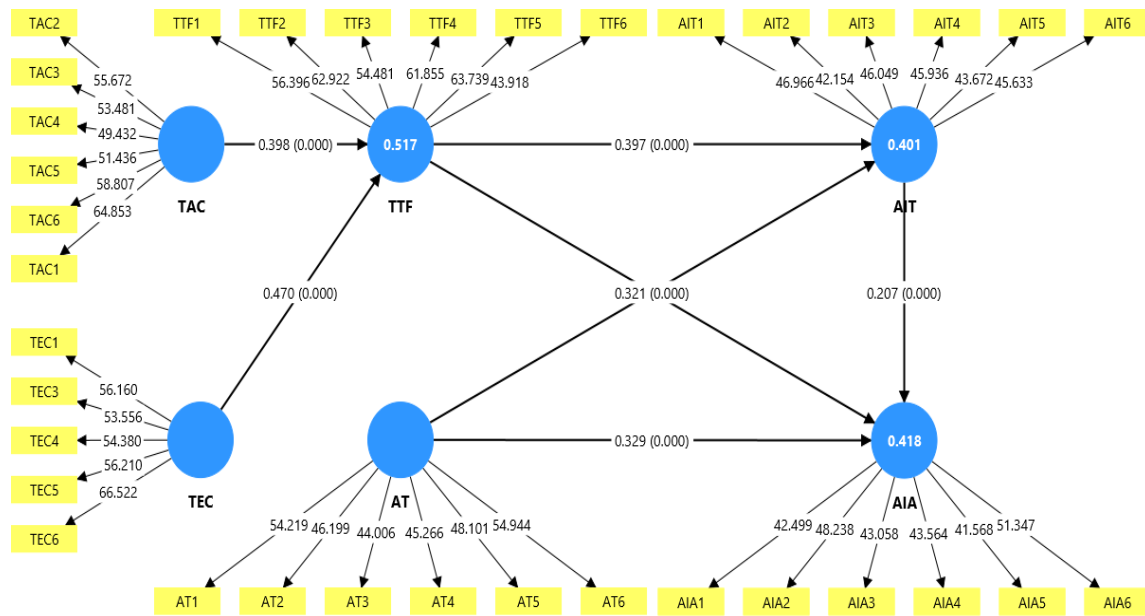


Figure 2. Path coefficient, P Value, & R2.

H	Exog.		Endo.	Original Sample (β)	Standard Deviation (STDEV)	t-value (C.R)	p-value	Result
H1	TAC		TTF	0.398	0.039	10.178	0.000**	Supported
H2	TEC		TTF	0.470	0.038	12.460	0.000**	Supported
H3	TTF		AIT	0.397	0.036	11.120	0.000**	Supported
H4	TTF		AIA	0.321	0.045	7.130	0.000**	Supported
H5	AIT		AIA	0.207	0.053	3.901	0.000**	Supported
H6	AT		AIT	0.433	0.035	12.290	0.000**	Supported
H7	AT		AIA	0.329	0.047	7.009	0.000**	Supported
H8	TTF--> AIT--> AIA			0.082	0.022	3.717	0.000**	Supported
H9	AT--> AIT--> AIA			0.090	0.025	3.616	0.000**	Supported

Table 7. Hypothesis Testing (Path Coefficient)

The results indicated that AI Trust had a significant impact on AI Adoption ($\beta=0.207$, $t=3.901$, $p<0.001$) as suggested in hypothesis 5. Trust was an important determinant though weaker than fit and transparency. Reliability, predictability, and moral acceptability of AI had a positive effect on willingness to trust AI's outputs. This aligns with the findings of (Afroogh et al., 2024; Choung et al., 2023; Robles & Mallinson, 2025), which highlighted accuracy, fairness, accountability, and institutional safeguards as pillars for trustworthy AI.

The hypothesis 6 was accepted stating that AI Transparency had a positive effect on AI Trust ($\beta=0.433$, $t=12.290$, $p<0.001$) and was the greatest predictor of trust. This finding aligns with (Fine Licht & Fine Licht, 2020; Lee & Cha, 2025; Schmidt et al., 2020) who stated that providing understandable explanations, appropriate disclosures and holding themselves accountable can enhance confidence and legitimacy. It should be seen in conjunction with, however, (Ngo, 2025), that warned that over technical disclosure might lead to cognitive overload. Transparency should thus be relevant, proportionate and adjusted to the user's expertise.

Hypothesis 7 also received support as there was a direct path between AI Transparency and AI Adoption ($\beta=0.329$, $t=7.009$, $p<0.001$). This is to assert that transparency is not only an ethical principle, but also a practical way to adopt it. Clear explanations enhance user control, decision validation and organisational legitimacy, in line with (Fine Licht & Fine Licht, 2020; Kaplan et al., 2024; Wanner et al., 2022)

Lastly, Hypotheses 8 and 9 were confirmed. AI Trust significantly mediated the effects of Task–Technology Fit ($\beta=0.082$, $t=3.717$, $p<0.001$) and AI Transparency ($\beta=0.090$, $t=3.616$, $p<0.001$) on AI Adoption. This complementarity of mediation effects indicates that fit and transparency facilitates the adoption directly, and simultaneously has a confidence-building effect. The results thus add to existing studies, by combining functional suitability, comprehensible system behaviour and trust in a single governmental AI-adoption framework.

7. Conclusion and future research

This study investigated the factors influencing AI adoption in Omani governmental ministries focusing on the Task–Technology Fit theory along with AI Transparency and AI Trust. Partial Least Squares Structural Equation Modelling (SEM) by SmartPLS was applied to analyse data obtained from the survey of different employees in the Ministry of Justice as well as in the Ministry of Transport, Communications and Information Technology and the Ministry of Health. Results of the assessment of the measurement model revealed that all indicators were reliable, internal consistency was satisfactory, convergent validity was satisfactory, and discriminant validity was satisfactory, and that bootstrapping results supported all seven direct hypotheses and both mediation hypotheses.

The results show that a mix of functional alignment, technological quality, transparency and trust are factors affecting the adoption of AI. The overall Task–Technology Fit model accounted for 51.7% of the variance. Task–Technology Fit was most strongly influenced by Technology Characteristics ($\beta=0.470$), followed by Task Characteristics ($\beta=0.398$), which suggests that the employee's perception of system reliability, accuracy, responsiveness, and accessibility play a crucial role in determining if AI can effectively meet their work needs.

The variance in AI Trust was explained by 40.1% of AI Transparency and Task–Technology Fit. AI Transparency had the highest effect on trust ($\beta=0.433$) and Task–Technology Fit also had a significant positive effect ($\beta=0.397$). These findings suggest that transparency and alignment of the functions of AI with task needs are positively associated with employees' trust in AI. The three factors of Task–Technology Fit, AI Transparency and AI Trust explained 41.8% of the variance in AI Adoption. The direct impacts of AI Transparency ($\beta=0.329$) and Task–Technology Fit ($\beta=0.321$) were greater than AI Trust ($\beta=0.207$), indicating that both transparency and task alignment are needed before employees fully integrate AI into their work.

Mediation analysis results also indicated that AI Trust was a partial mediator between Task–Technology Fit and AI Adoption and AI Transparency and AI Adoption. The two indirect effects were positive and significant, thus supporting complementary mediation. This finding expands Task–Technology Fit research, as it shows that functional alignment is a direct contributor to technology adoption and also increases confidence in the AI. It also sets transparency as a mechanism of adoption as well as a precondition to trust.

The findings indicate the need to not see the use of AI as a purely technical process of implementation in government ministries. This involves strategic integration of AI tools with business functions, clear interpretation of AI-generated data, conveying the limitations of AI, and implementing organizational practices that enhance staff trust. Therefore, alongside technological investment, training, user participation, explainability features and human oversight should be included.

Future study might be directed to private sector organisations, state owned enterprises and other governmental institutions to check the generalisability of the model. Longitudinal studies can be conducted to see how trust and adoption changes over time with the use of AI systems. Further research might be conducted to examine moderating variables like digital competence, organisational culture, perceived risk, voluntariness of use or leadership support. Qualitative and mixed-method research studies also can offer a more detailed understanding of employees' perceptions of transparency of AI, establishing trust, and addressing implementation issues in practice.

8. Implementations

8.1 Theoretical Contributions

This study contributes to the research on the adoption of AI by integrating the Task–Technology Fit theory and AI Transparency and AI Trust in one explanatory model. The research indicates that the adoption of AI requires a combination of AI capabilities fitting to the work needs of employees and user-friendliness and trustworthiness of the system. Task Characteristics and Technology Characteristics were found to have a significant effect on Task–Technology Fit, demonstrating the importance of both work demands and system attributes in understanding the adoption outcomes.

The study also expands on the Task–Technology Fit theory by showing that the impact of functional alignment is partially mediated by AI Trust and that AI Trust is directly linked to AI Adoption. A well-matched system thus facilitates use in addition to promoting task performance, as it conveys competence and dependability. AI Transparency also had a direct and indirect impact on adoption which acted as a behaviour and confidence building mechanism.

8.2 Managerial and Policy Implications

The results contain several implications for the Omani governmental ministries. The first step in implementing AI should be to thoroughly understand the workflows, information needs, decision-making authorities, and constraints within each department. Systems should be tailored to the needs of each system function and not be applied consistently across units.

The highest ratings for the Technology Characteristics suggest that ministries should focus on the accuracy, reliability, responsiveness, availability, and interface usability of the system as key factors in the Task–Technology Fit. Structured user feedback and continuous technical assessment may help to improve in time.

Moreover, transparency must also be part of the process of procuring, developing, and governing AI. Clear explanations are needed regarding what data will be used, how data will be outputted, limitations of the system, accountability, and the review process. Confidence and responsible use can be further enhanced through training, employee participation and human oversight.

9. Research Limitations

The study was conducted in three Omani government ministries, and its findings may not be applicable to other institutions, sectors or nations. It is a cross-sectional study and therefore does not allow for the full determination of causality or changes in trust and adoption. Common-method and social-desirability bias may also have occurred as a result of the self-report data. Future research needs should be based on longitudinal designs, objective usage measurements, multiple groups of respondents and comparative samples of private and public organisations.

10. Ethical Statement/Approval

All participation was voluntary and informed consent was obtained. No sensitive identifying information was collected. Responses were anonymised, confidential, securely stored and used for academic research only.

REFERENCES

1. Afroogh, S., Akbari, A., Malone, E., Kargar, M., & Alambeigi, H. (2024). Trust in AI: progress, challenges, and future directions. *Humanities and Social Sciences Communications*, 11(1). <https://doi.org/10.1057/s41599-024-04044-8>
2. Agrawal, A., Gans, J. S., & Goldfarb, A. (2024). Artificial intelligence adoption and system-wide change. *Journal of Economics and Management Strategy*, 33(2), 327–337. <https://doi.org/10.1111/jems.12521>
3. Akben, M., & Dong, S. (2025). A Paradox of Fit: How Job Complexity Shapes AI Self-Efficacy and AI Adoption Through a Curvilinear Mechanism. *Behavioral Sciences*, 15(12). <https://doi.org/10.3390/bs15121659>
4. Al-Zubaidi, R., Ariffin, K. A. B. M., Abdulsamad, A., Raqee, A., Ismail, I. S., & Ahmad, K. A. (2022). The Effect of Self-efficacy on Sustainable Development: The PetroMasila in Yemen. *Advances in Social Sciences Research Journal*, 9(12), 35–49. <https://doi.org/10.14738/assrj.912.13555>
5. Al-Zubaidi, R., Ariffin, K. A. B. M., Ismail, I. S., Ahmad, K. A., Raqee, A., & Abdulsamad, A. (2023). Sustainable Development Through Effective Project Management : The Petromasila in Yemen. *Advances in Social Sciences Research Journal*, 10(3).
6. Al-Zubaidi, R., Ateeq, A., Abdulsamad, A., Ibrahim, S. B., Ahmed, H. R. H. A., & Milhem, M. (2025). Market Orientation and SMEs Performance: Unraveling the Mediating Effects of Innovation Capability Amidst Environmental Uncertainty. *Studies in Systems, Decision and Control*, 234, 859–872. https://doi.org/10.1007/978-3-031-84636-6_77
7. Alkaabi, A., Jabeen, F., Dwivedi, A., & Jose, S. (2026). Artificial intelligence adoption in the service industry: investigating the role of perceived usefulness and ease of use. *International Journal of Productivity and Performance Management*, 75(4), 1049–1071. <https://doi.org/10.1108/IJPPM-06-2024-0369>
8. Allegrini, V., Monteduro, F., & Del Prete, F. (2022). Explaining the Use of Performance Information by Public Managers: Do Task-Related Factors Matter? *Public Organization Review*, 22(4), 949–965. <https://doi.org/10.1007/s11115-021-00556-y>
9. Angelopoulos, G., Lacroix, D., Wullenkord, R., Rossi, A., Rossi, S., & Eyssel, F. (2025). Measuring transparency in intelligent robots. *Scientific Reports*, 15(1). <https://doi.org/10.1038/s41598-025-29685-w>
10. Arora, M., & Mittal, A. (2025). Employees' change in perception when artificial intelligence integrates with human resource management: a mediating role of AI-tech trust. *Benchmarking*, 32(6), 1884–1908. <https://doi.org/10.1108/BIJ-11-2023-0795>
11. Aslam, J., Saleem, A., & Lai, K. H. (2025). Supply Chain Management in the Era of Generative AI (ChatGPT): Technology Fit and Psychological Drivers of Adoption. *IEEE Transactions on Engineering Management*. <https://doi.org/10.1109/TEM.2025.3605823>
12. Bentler, P. M., & Hu, L. (1998). Fit indices in covariance structure modeling: Sensitivity to underparameterized model misspecification. *Psychological Methods*, 3(4), 424–453.
13. Blaurock, M., Büttgen, M., & Schepers, J. (2024). Designing Collaborative Intelligence Systems for Employee-AI Service Co-Production. *Journal of Service Research*. <https://doi.org/10.1177/10946705241238751>
14. Campbell, D. J. (1988). Task Complexity: A Review and Analysis. *Academy of Management Review*, 13(1), 40–52. <https://doi.org/10.5465/amr.1988.4306775>
15. Cane, S., & McCarthy, R. (2009). Analyzing the factors that affect information systems use: A task-technology fit meta-analysis. *Journal of Computer Information Systems*, 50(1), 108–123. <https://doi.org/10.1080/08874417.2009.11645368>
16. Chavarnakul, T., Lin, Y. C., Khan, A., & Chen, S. C. (2024). Exploring the Determinants and Consequences of Task-Technology Fit: A Meta-Analytic Structural Equation Modeling Perspective. *Emerging Science Journal*, 8(1), 77–94. <https://doi.org/10.28991/ESJ-2024-08-01-06>
17. Chen, P. S., Yu, C. J., & Chen, G. Y. H. (2015). Applying Task-Technology Fit Model to the Healthcare Sector: a Case Study of Hospitals' Computed Tomography Patient-Referral Mechanism. *Journal of Medical Systems*, 39(8). <https://doi.org/10.1007/s10916-015-0264-9>
18. Chin, W. W. (2010). How to Write Up and Report PLS Analyses. In *Handbook of Partial Least Squares* (pp. 655–690). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-540-32827-8_29
19. Choung, H., David, P., & Ross, A. (2023). Trust in AI and Its Role in the Acceptance of AI Technologies. *International Journal of Human-Computer Interaction*, 39(9), 1727–1739. <https://doi.org/10.1080/10447318.2022.2050543>
20. Cohen, J. (2013). Statistical Power Analysis for the Behavioral Sciences. In *Routledge*. <https://doi.org/10.4324/9780203771587>
21. Dabbous, A., Aoun Barakat, K., & Merhej Sayegh, M. (2022). Enabling organizational use of artificial intelligence: an employee perspective. *Journal of Asia Business Studies*, 16(2), 245–266. <https://doi.org/10.1108/JABS-09-2020-0372>
22. De Brito Duarte, R., Correia, F., Arriaga, P., & Paiva, A. (2023). AI Trust: Can Explainable AI Enhance Warranted Trust? *Human Behavior and Emerging Technologies*, 2023. <https://doi.org/10.1155/2023/4637678>
23. Fernández-Macías, E., & Bisello, M. (2022). A Comprehensive Taxonomy of Tasks for Assessing the Impact of New Technologies on Work. *Social Indicators Research*, 159(2), 821–841. <https://doi.org/10.1007/s11205-021-02768-7>

24. Fine Licht, K. de, & Fine Licht, J. de. (2020). Artificial Intelligence, Transparency, and Public Decision-Making. *Ai & Society*.
25. Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS Quarterly: Management Information Systems*, 19(2), 213–233. <https://doi.org/10.2307/249689>
26. Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2–24. <https://doi.org/10.1108/EBR-11-2018-0203>
27. Hair, J. F., Sarstedt, M., Hopkins, L., & Kuppelwieser, V. G. (2014). Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research. *European Business Review*, 26(2), 106–121. <https://doi.org/10.1108/EBR-10-2013-0128>
28. Horani, O. M., Al-Adwan, A. S., Yaseen, H., Hmoud, H., Al-Rahmi, W. M., & Alkhalifah, A. (2025). The critical determinants impacting artificial intelligence adoption at the organizational level. *Information Development*, 41(3 Special Issue: “Artificial Intelligence initiatives”), 1055–1079. <https://doi.org/10.1177/02666669231166889>
29. Johnson, D. (2026). Citizen-Centric Approaches to AI in Government Programs: Lessons From Experimental Studies. *Public Administration Review*, 86(4), 982–1000. <https://doi.org/10.1111/puar.70077>
30. Kalyar, M. N., Rafi, N., & Kalyar, A. N. (2013). Factors affecting corporate social responsibility: An empirical study. *Systems Research and Behavioral Science*, 30(4), 495–505. <https://doi.org/10.1002/sres.2134>
31. Kaplan, S., Uusitalo, H., & Lensu, L. (2024). A unified and practical user-centric framework for explainable artificial intelligence. *Knowledge-Based Systems*, 283. <https://doi.org/10.1016/j.knosys.2023.111107>
32. Khalil, E., & Al-Ali, F. A. (2026). AI adoption in government public relations: Technology acceptance, social influence, and organizational dynamics in the UAE. *Public Relations Inquiry*, 15(1 Special Issue: Public Relations in the Middle East and North Africa: Critical Perspectives), 31–51. <https://doi.org/10.1177/2046147X251383106>
33. Lee, C., & Cha, K. (2025). Toward the Dynamic Relationship Between AI Transparency and Trust in AI: A Case Study on ChatGPT. *International Journal of Human-Computer Interaction*, 41(13), 8086–8103. <https://doi.org/10.1080/10447318.2024.2405266>
34. Lv, Z., Tang, C., Zheng, Y., & Yang, X. (2026). Proactive Interaction of Artificial Intelligence Agents in Intelligent Assistive Systems: Mechanisms and Impacts. *International Journal of Human-Computer Interaction*, 42(10), 7609–7629. <https://doi.org/10.1080/10447318.2025.2560518>
35. Maragno, G., Tangi, L., Gastaldi, L., & Benedetti, M. (2023). Exploring the factors, affordances and constraints outlining the implementation of Artificial Intelligence in public sector organizations. *International Journal of Information Management*, 73. <https://doi.org/10.1016/j.ijinfomgt.2023.102686>
36. Marikyan, D., Papagiannidis, S., Rana, O. F., Ranjan, R., & Morgan, G. (2022). “Alexa, let’s talk about my productivity”: The impact of digital assistants on work productivity. *Journal of Business Research*, 142, 572–584. <https://doi.org/10.1016/j.jbusres.2022.01.015>
37. McGrath, M. J., Lack, O., Tisch, J., & Duenser, A. (2025). Measuring trust in artificial intelligence: validation of an established scale and its short form. *Frontiers in Artificial Intelligence*, 8. <https://doi.org/10.3389/frai.2025.1582880>
38. Mercuri, F., Quaglieri, L., Ramírez-Hurtado, J. M., & Quattrociochi, B. (2025). Technological, organizational and environmental determinants influencing the intention to adopt GEN-AI of public sector organizations: a cross-country comparative analysis. *European Journal of Innovation Management*, 1–26. <https://doi.org/10.1108/EJIM-03-2025-0359>
39. Mikhaylov, S. J., Esteve, M., & Campion, A. (2018). Artificial intelligence for the public sector: Opportunities and challenges of cross-sector collaboration. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 376(2128). <https://doi.org/10.1098/rsta.2017.0357>
40. Ngo, V. M. (2025). Balancing AI transparency: Trust, Certainty, and Adoption. *Information Development*. <https://doi.org/10.1177/02666669251346124>
41. Park, C. (2019). Exploring a New Determinant of Task Technology Fit: Content Characteristics. *Journal of International Technology and Information Management*, 27(3), 100–118. <https://doi.org/10.58729/1941-6679.1385>
42. Parsons, C. S., Zuiderwijk, A., Orchard, N. A., Oosterhoff, J. H. F., & de Reuver, M. (2025). Applying Task-Technology Fit Model to the Healthcare Sector: a Case Study of Hospitals’ Computed Tomography Patient-Referral Mechanism. *BMC Medical Informatics and Decision Making*, 25(1). <https://doi.org/10.1186/s12911-025-03237-8>
43. Regona, M., Yigitcanlar, T., Hon, C., & Teo, M. (2026). Building Trust in Artificial Intelligence: A Systematic Review through the Lens of Trust Theory. *ACM Computing Surveys*, 58(9). <https://doi.org/10.1145/3789256>
44. Ren Kon, M. W., Abisheganaden, J., & Ang, G. Y. (2026). Adoption of artificial intelligence in healthcare: A strategic transformation framework. *Hong Kong Journal of Emergency Medicine*, 33(1). <https://doi.org/10.1002/hkj2.70077>
45. Robles, P., & Mallinson, D. J. (2025). Artificial intelligence technology, public trust, and effective governance. *Review of Policy Research*, 42(1), 11–28. <https://doi.org/10.1111/ropr.12555>
46. Russo, D. (2024). Navigating the Complexity of Generative AI Adoption in Software Engineering. *ACM Transactions on Software Engineering and Methodology*, 33(5). <https://doi.org/10.1145/3652154>
47. Salwin, M., Kocot, M., Kwasek, A., Trzaskowska-Dmoch, A., Pałęga, M., & Kopytowski, A. (2026). Assessing the Determinants of Trust in AI Algorithms in the Conditions of Sustainable Development of the Organization. *Sustainability (Switzerland)*, 18(2). <https://doi.org/10.3390/su18020776>
48. Schmidt, P., Biessmann, F., & Teubner, T. (2020). Transparency and trust in artificial intelligence systems. *Journal of Decision Systems*, 29(4), 260–278. <https://doi.org/10.1080/12460125.2020.1819094>

49. Selten, F., & Klievink, B. (2024). Organizing public sector AI adoption: Navigating between separation and integration. *Government Information Quarterly*, 41(1). <https://doi.org/10.1016/j.giq.2023.101885>
50. Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J. H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. *European Journal of Marketing*, 53(11), 2322–2347. <https://doi.org/10.1108/EJM-02-2019-0189>
51. Smith, M., Prabhakar, G., Nisar, T. M., & Tseng, H. T. (2025). Adoption of AI by the HR function in the civil service. *Employee Relations*, 47(1), 104–126. <https://doi.org/10.1108/ER-02-2024-0096>
52. Sun, H., Liu, W., Wu, D., Yu, G., & Yao, M. (2025). *Revisiting Trust in the Era of Generative AI: Factorial Structure and Latent Profiles*. <https://arxiv.org/pdf/2510.10199>
53. Ulfa, S., Surahman, E., Fatawi, I., & Tsukasa, H. (2024). Task-Technology Fit Analysis: Measuring the Factors that influence Behavioural Intention to Use the Online Summary-with Automated Feedback in a MOOCs Platform. *Electronic Journal of E-Learning*, 22(1), 63–77. <https://doi.org/10.34190/ejel.22.1.3094>
54. von Eschenbach, W. J. (2021). Transparency and the Black Box Problem: Why We Do Not Trust AI. *Philosophy and Technology*, 34(4), 1607–1622. <https://doi.org/10.1007/s13347-021-00477-0>
55. Wang, Q., Wang, Y., & Amini, M. (2026). Associations of task technology fit and perceived usefulness with responsible generative AI use among university students. *Scientific Reports*, 16(1). <https://doi.org/10.1038/s41598-025-32692-6>
56. Wanner, J., Herm, L. V., Heinrich, K., & Janiesch, C. (2022). The effect of transparency and trust on intelligent system acceptance: Evidence from a user-based study. *Electronic Markets*, 32(4), 2079–2102. <https://doi.org/10.1007/s12525-022-00593-5>
57. Yang, M. M., Lu, Y., & Cooke, F. L. (2026). Demystifying AI for the Workforce: The Role of Explainable AI in Worker Acceptance and Management Relations. *Journal of Management Studies*, 63(2), 438–472. <https://doi.org/10.1111/joms.70039>
58. Yew, W. C., Kong, S. M., Awang, A. H., & Yi, G. R. (2022). Developing a Conceptual Model for the Causal Effects of Outdoor Play in Preschools Using PLS-SEM. *Sustainability (Switzerland)*, 14(6). <https://doi.org/10.3390/su14063365>
59. Yu, L., Li, Y., & Fan, F. (2023). Employees' Appraisals and Trust of Artificial Intelligences' Transparency and Opacity. *Behavioral Sciences*, 13(4). <https://doi.org/10.3390/bs13040344>
60. Zeng, X., Li, S., & Yousaf, Z. (2022). Artificial Intelligence Adoption and Digital Innovation: How Does Digital Resilience Act as a Mediator and Training Protocols as a Moderator? *Sustainability (Switzerland)*, 14(14). <https://doi.org/10.3390/su14148286>
61. Zhang, X., Qi, Z., Ma, L., & Zhang, G. (2025). Assessing the Curvilinear Relationship in Employee Digital Performance: A Task-Technology Fit Perspective. *International Journal of Human-Computer Interaction*, 41(4), 2615–2633. <https://doi.org/10.1080/10447318.2024.2327181>
62. Zhou, T. (2012). Examining mobile banking user adoption from the perspectives of trust and flow experience. *Information Technology and Management*, 13(1), 27–37. <https://doi.org/10.1007/s10799-011-0111-8>