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Determinants of Public Sector Managers' Intentions to Adopt AI in the Workplace

Khalid Majrashi, Digital Transformation and Information Center, Institute of Public Administration, Riyadh, Saudi Arabia*
https://orcid.org/0000-0001-6986-5334

ABSTRACT

This study investigated the determinants of public sector managers' intentions to adopt artificial intelligence (AI) systems within their organizations. An extended technology acceptance model (TAM) was developed, incorporating additional constructs including fairness, humanity, reliability, safety, transparency, accountability, privacy, security, trust, social norms, tolerance, impact, and isomorphic pressure. A survey was conducted among 330 public sector managers, and the data were analyzed using linear regression tests to evaluate the model. The results showed significant positive influences of both perceived usefulness and perceived impact on managers' attitudes and behavioral intentions toward AI adoption. Isomorphic pressure was also a significant determinant of managers' behavioral intentions toward adopting AI systems. Our findings also indicated that perceptions related to AI ethical principles, such as transparency, privacy, and security, influenced managers' trust in AI systems.

KEYWORDS

AI Adoption, AI Ethics, Artificial Intelligence, Attitudes, Behavioral Intentions, Managers, Public Sector, Technology Acceptance Model, Trust in AI, Workplace

INTRODUCTION

The definition of AI lacks a universal consensus, with varying perspectives on its capabilities. AI is often conceptualized as machines or computer systems mimicking human thought and behavior, either by performing tasks requiring human-like intelligence, such as decision-making, or by employing rational thinking based on logic and the careful consideration of options (Russell & Norvig, 2021). AI can be classified as "weak AI", excelling in specific domains but incapable of autonomously solving problems outside those areas (Wamba et al., 2021), while speculation surrounds the potential for AI to achieve singularity, becoming "conscious/self-aware AI" if it surpasses human intelligence (Kaplan & Haenlein, 2019).

Artificial Intelligence systems are revolutionizing workplace practices by injecting unprecedented value into complex processes and decision-making frameworks. This wave of technological advancement is not confined to the private sector; it is also making significant strides within the public sector, as evidenced by the growing body of research (Wirtz et al., 2019). Despite high expectations that AI will enhance the public sector's operational efficiency, services and decision-making quality,

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*Corresponding Author

the integration of AI technologies into public organizations has been modest (Selten & Klievink, 2024). Cutting-edge AI technologies, including large language models, computer vision, generative AI, robotics, natural language processing (NLP), and machine learning algorithms, are evolving at a breakneck pace. These advancements enable AI to tackle increasingly sophisticated tasks, paving the way for its potential to significantly improve the efficiency and effectiveness of public sector operations and services (Madan & Ashok, 2023; Margetts & Dorobantu, 2019; Selten & Klievink, 2024). However, many public organizations find themselves at a crossroads, eager to harness these innovative technologies yet hindered by the rapid technological evolution of AI. This challenge is compounded by a range of barriers that impede the adoption and effective utilization of AI within the public sector. Such barriers include, but are not limited to, issues related to data governance, ethical considerations, and a lack of technical expertise for implementing AI solutions (Kempeneer & Heylen, 2023; Madan & Ashok, 2023; Mergel et al., 2023; Wirtz et al., 2019).

Managers hold a critical position within organizations, exerting substantial influence over the adoption of new technologies (Gagnon et al., 2000). Despite their significant impact, the perspectives of managers are often overlooked (Nielsen et al., 2019; Ullah et al., 2021). Research indicates that transformative leadership traits play a crucial role in influencing AI adoption in the public sector (Madan & Ashok, 2023). Chief information officers (CIOs) are also identified as key players in the adoption and dissemination of AI, requiring not just technical expertise but also political savvy to shape the design of enterprise systems within and across government agencies (Madan & Ashok, 2023). However, studies reveal that public managers, including CIOs, often make decisions regarding the use of AI and other technologies based on pre-existing attitudes and cognitive frames (Criado et al., 2021; Guenduez et al., 2020; Kempeneer & Heylen, 2023). This highlights the importance of understanding their attitudes and intentions to effectively address their concerns and potentially facilitate more successful AI implementations in public organizational settings.

Studies have also highlighted that managers in public organizations are increasingly adopting AI systems (de Sousa et al., 2019). However, the factors driving public sector managers' intentions to adopt AI in their workplaces are not well understood. While the attitudes and intentions of managers utilizing AI in the private sector have been studied considerably (Cao et al., 2021), there remains a lack of research investigating the intentions of managers to adopt AI in the public sector. This study aims to bridge this knowledge gap by exploring the determinants of AI adoption among managers in the public sector.

In this study, the author developed a model aimed at predicting public managers' intentions to adopt AI systems within their workplaces, which is rooted in the TAM (Davis, 1985, 1989). The AI adoption model for public sector managers (AI-AMPM) extends TAM by integrating additional AI ethics and socio-organizational predictive factors (see Figure 1). These additional factors are derived from the literature and AI ethics principles and guidelines. These factors include fairness, humanity, reliability, safety, transparency, accountability, privacy, security, and trust, alongside social norms, tolerance, impact, and isomorphic pressure (Choudhury & Shamszare, 2023; Choung et al., 2023; DiMaggio & Powell, 1983; European Commission, 2019; Farson & Keyes, 2003; Hawley, 1968; Kriegesmann et al., 2005; Majrashi, 2022; OECD, 2019; SDAIA, 2023a; Shin, 2020; Slutzky, 2012). Each of these factors—as perceived by managers—was considered for its potential influence on AI adoption within the public sector. The model was validated through a study focused on understanding the intentions of public sector managers in Saudi Arabia to adopt AI systems.

Overall, the research findings affirmed the relevance of the original TAM constructs in the context of AI system adoption among public sector managers. The results also highlighted the significant role of perceived impact in influencing managers' attitudes and intentions toward AI adoption. Isomorphic pressure was also identified as a key determinant in shaping public sector managers' intentions to adopt AI systems within their organizations. Additionally, perceived transparency, perceived privacy, and perceived security were found to have a strong predictive power for managerial trust in AI systems.

The findings also indicated that while trust influences managers' attitudes and behavioral intentions toward AI adoption, its overall impact is relatively modest.

This paper begins with an overview of the background and related literature. It subsequently presents the theoretical basis, hypotheses, and research model. This is followed by a detailed description of the methodology employed. The results are then presented and discussed. The paper concludes by summarizing the overall findings, addressing the study's limitations, and suggesting directions for future research.

BACKGROUND

Overview of AI in the Public Sector

The recent evolution in AI has unlocked a diverse array of possibilities for its application within the public sector (Berryhill et al., 2019; Wirtz et al., 2019; Zuiderwijk et al., 2021). Wirtz et al. (2019) conducted a thorough analysis, identifying ten pivotal AI application areas in the public sector, such as AI process automation and speech analytics, each offering unique benefits and functional propositions. As an illustration, in the AI process automation domain, public sector use cases include expedited and higher-quality processing of immigration application forms (Chun, 2007) and enhanced user experiences through smart automation of repetitive tasks like data entry (Jefferies, 2016).

The scope of AI's impact extends across various public sector functions, including decision support, transportation, healthcare, education, environment, energy, information and communication technologies, public safety, defense, national security, judiciary, immigration, customs, and border protection (Berryhill et al., 2019; de Sousa et al., 2019; Denford et al., 2024). Recent advancements in AI, such as ChatGPT and similar generative artificial intelligence technologies, have the transformative potential to revolutionize various public sector fields (Adıgüzel et al., 2023; Xiao et al., 2023). Despite these promising developments, research on AI in the public sector remains relatively limited, particularly when compared to the wealth of studies in the private sector (Campion et al., 2022; de Sousa et al., 2019). While research in private sector settings offers valuable insights, it cannot fully address the unique challenges and characteristics of the public sector.

There are several challenges associated with the usage of AI in the public sector. Wirtz et al. (2019) identified four major dimensions of these challenges. The first challenge relates to the demanding nature of implementing AI technology within the public sector, involving significant infrastructural adjustments. The second challenge concerns managing and controlling AI technology given its potential social and economic impacts. The third challenge focuses on ethical considerations in the development and use of AI applications, underlining the importance of integrating ethical principles to ensure AI systems' moral behavior. The last challenge, termed "AI society," addresses the transformation of social life and human interactions by AI, spotlighting the social challenges that emerge from these changes. As AI becomes a more prominent focus in public administration research priorities (McDonald III et al., 2022), there is an urgent need for more comprehensive research in public sector settings to fully realize the benefits of AI adoption and tackle its unique challenges.

Government Initiatives for AI in the Public Sector: The Case of Saudi Arabia

Several countries have recognized the significant value of AI for public use and have launched various costly AI initiatives (Berryhill et al., 2019; Holdren & Smith, 2016; Knight, 2017). These initiatives aim to enhance efficiency, decision-making, citizen and business relationships, and contribute to achieving sustainable development goals (SDGs) (Berryhill et al., 2019). Globally, many national AI strategies or equivalent guiding policies have been developed to establish strategic visions, approaches, priorities, and goals for artificial intelligence, with some cases also outlining a detailed roadmap for their accomplishment (Berryhill et al., 2019; Denford et al., 2024). National AI strategies can encompass both public and private sector policies (Denford et al., 2024). However, it is noteworthy that many of these strategies specifically emphasize the adoption and utilization of AI in the public sector, targeting innovation and transformation (Berryhill et al., 2019; Galindo et al., 2021).

Saudi Arabia, the context of this study, is actively striving to leverage the power of artificial intelligence to benefit its economy, enhance business and public services, and position itself as a global leader in artificial intelligence and data (SDAIA, 2020a). To spearhead these efforts, the Saudi government established the Saudi Authority for Data and Artificial Intelligence (SDAIA), which has played a pivotal role in formulating a national strategy for data and artificial intelligence (SDAIA, 2020b, n.d.-a). Notably, this strategy places a strong emphasis on the public sector, aiming to promote the adoption of data and AI technologies to create a more efficient and effective government (SDAIA, 2020a, 2020b). SDAIA has further developed comprehensive regulations, policies, standards, and guidelines for data management (SDAIA, n.d.-c), along with AI ethics principles and generative Al guidelines (SDAIA, n.d.-b), as well as data indexes to evaluate the maturity and adherence of data practices within the public sector (SDAIA, 2023b). Additionally, ambitious initiatives have been launched by SDAIA to enhance the skillsets of individuals in AI and facilitate the integration of AI technologies within public sector organizations.

The Digital Government Authority (DGA) in Saudi Arabia is also providing guidance on adopting emerging technologies, including AI, in government entities (DGA, 2022) and has developed an index to measure readiness to adopt these technologies at the government agency level (DGA, 2023). The 2023 report on readiness to adopt emerging technologies in Saudi government agencies highlighted several success stories of AI adoption across different government sectors (DGA, 2023). However, despite the success cases in AI adoption in the public sector worldwide, factors that may hinder AI adoption in other cases are often overlooked in many government reports (Boyd & Wilson, 2017; Wirtz et al., 2019). While government efforts toward AI adoption in the public sector tend to emphasize practical applications, this study seeks to contribute scientifically by investigating factors influencing public sector managers' intentions regarding AI adoption. It develops an AI adoption model for public sector managers and validates it in the context of Saudi Arabia, a country actively pursuing AI integration in its public sector.

AI Adoption in Public Sector Organizations

The adoption of Information Technology (IT) innovations is a well-explored area in information systems research. At the organizational level, AI adoption represents a distinct paradigm within the broader landscape of IT innovation adoption (Neumann et al., 2023; Selten & Klievink, 2024). However, in contrast to other IT innovations, AI adoption presents substantially greater challenges than other digital technologies, which are known for their simplicity in implementation, deployment, and usage (Jöhnk et al., 2021; Neumann et al., 2023; Selten & Klievink, 2024). To comprehend the various factors influencing AI adoption, studies leverage widely accepted theoretical models in information systems research, such as TAM (Wang et al., 2021), the unified theory of acceptance and use of technology (UTAUT) (Cao et al., 2021), the technology threat avoidance theory (TTAT) (Cao et al., 2021), and the technology, organization, and environment (TOE) framework (Madan & Ashok, 2023; Neumann et al., 2023).

In the context of AI adoption in public administration, Madan and Ashok (2023) conducted a systematic literature review utilizing the TOE framework to identify factors influencing AI adoption and diffusion. In the technological context, they underscored the importance of digital maturity, IT capabilities, and perceived benefits. The organizational context emphasized the importance of cultivating an innovative organizational culture, exhibiting transformative leadership traits, and overcoming inertia by addressing challenges like bureaucracy. The environmental context encompassed vertical pressures, such as policy signals and mandates for digital service delivery and automation, and horizontal pressures, including intergovernmental competition, citizen demands, and industry influences. Madan and Ashok (2023) also identified the absorptive capacity as a global theme that permeates all TOE contexts. Absorptive capacity is pivotal in AI adoption, encompassing factors such as reliance on existing infrastructure, dynamic capabilities, and knowledge management practices.

Factors influencing AI adoption can vary based on an organization's stage in the AI adoption process or its levels of AI maturity. Neumann et al. (2023), utilizing the TOE framework, conducted a comparative case study involving eight Swiss public organizations. Their findings indicated that the significance of technological and organizational factors differs depending on the organization's stage in the AI adoption process, with environmental factors generally playing a less critical role. Their study advocates for more research on the drivers and barriers to AI adoption, emphasizing the need to explore different factors and to expand the TOE framework by incorporating a temporal dimension. This addition aims to observe distinct stages of organizational AI maturity more effectively.

Factors influencing AI adoption can also vary based on the adoption mode or approach. For instance, Selten and Klievink (2024) examined how public organizations strategically manage AI adoption. They identified two modes of AI adoption: 1) structural separation, involving the establishment of separate departments for data science teams, and 2) contextual integration, which integrates these teams into existing operational departments. Each mode was associated with distinct barriers to AI adoption. For structurally separate data teams, the barriers included inadequate IT infrastructure support for AI applications, and the AI systems often lacked alignment with operational and strategic goals, leading to insufficient support from both frontline and executive levels. In the contextually integrated approach, common barriers included compliance with ethical and legal frameworks, lack of robustness, and insufficient technical expertise.

Given the multitude of factors influencing AI adoption in public sector organizations, as discussed above, understanding the intentions of public sector managers regarding AI adoption becomes imperative. Their attitudes and decisions play a crucial role in affecting the adoption and integration of AI technologies within their organizations.

Managerial Perceptions, Attitudes, and Intentions Toward AI Adoption

The perceptions, attitudes, and intentions of managers regarding AI adoption in the public sector have received limited attention. Criado et al. (2021) highlighted that the literature on AI in the public sector often draws heavily from experiences, cases, ideas, and results from the private sector. Consequently, they investigated how CIOs perceive AI in the public sector, recognizing them as key figures in implementing emerging technologies within government organizations (Ganapati & Reddick, 2012). A survey targeting national/federal CIOs in Mexico and Spain revealed a consensus among CIOs from both countries that AI in the public sector closely resembles its application in the private sector, with a expressed willingness to integrate AI into public sector operations. Although this study offers valuable insights into CIOs' general perspectives on AI adoption in public sector in specific national contexts, it underscores the need for further research to explore the specific factors influencing AI adoption in the public sector as perceived by all public managers, not just CIOs, to provide a more comprehensive understanding of the subject.

In the context of the private sector, Cao et al. (2021) conducted a study focusing on managers' attitudes and intentions in utilizing AI for decision-making. Their integrated AI acceptance-avoidance model (IAAAM), based on the foundational principles of the unified theory of acceptance and use of technology (UTAUT), technology threat avoidance theory (TTAT), and other pertinent factors, considers both positive and negative influences collectively shaping managers' attitudes and behavioral intentions toward AI adoption. Recognizing the importance of encompassing both benefits and concerns in understanding perceptions of information technologies (Breward et al., 2017), the model incorporated elements like peer influence, performance expectancy, personal well-being concerns, and perceived severity. Tested through a survey of business managers in the United Kingdom, the model demonstrated comprehensiveness in explaining and predicting managers' attitudes and behavioral intentions toward AI usage. While distinctions exist between public and private sector organizations, there is a crucial need for a comprehensive model to understand intentions toward AI adoption among public sector managers.

THEORY AND HYPOTHESIS

Technology Acceptance Model (TAM)

TAM, created by Davis (1985), is a valuable framework for understanding users' intentions to accept and utilize technology (Al-Gahtani, 2001; Pikkarainen et al., 2004). It primarily seeks to identify the factors that drive the acceptance of technological and information systems. With its broad acceptance in information system research, TAM has been extensively applied across various domains such as information and cybersecurity, internet banking, cloud computing, and AI technologies (Al-Harby et al., 2009; Al-Sharaf et al., 2016; Alharbi, 2012; Giovanis et al., 2012; James et al., 2006; Lee, 2009; Majrashi, 2022; Park & Kim, 2014; Simon, 2007). Empirical studies have demonstrated the model's robustness in predicting individual intentions to accept and use information systems, outperforming other models (Mathieson, 1991).

Perceived usefulness and perceived ease of use are two fundamental determinants in TAM (Davis, 1989; Davis et al., 1989). Perceived usefulness is defined as the person's belief that "using a particular system would enhance his or her job performance within an organizational context," while perceived ease of use refers to "the degree to which a person believes that using a particular system would be free of effort" (Davis, 1989, p. 320). TAM assumes that these two factors significantly impact user attitudes toward technology (Davis, 1985; Majrashi, 2022). It also assumes that user's perception of ease of use affects their perception of usefulness (Davis, 1985). It further suggests that an individual's intention to adopt and use a system is determined by their attitudes toward the technology and its perceived usefulness (Davis, 1985; Majrashi, 2022). The model concludes with the idea that actual system use is a direct result of this behavioral intention (Majrashi, 2022).

Our research, grounded in the foundational elements of TAM, employs behavioral intention as the dependent variable in alignment with numerous preceding studies, e.g., Majrashi (2022). From this established theoretical base, we derive the following hypotheses for examination within the context of our research:

H1: Perceived usefulness positively influences managers' attitude toward adopting AI systems in public sector organizations.
H2: Perceived ease of use positively influences managers' attitude toward adopting AI systems in public sector organizations.
H3: Perceived ease of use positively influences public sector managers' perception of the usefulness of AI systems.
H4: Perceived usefulness positively influences managers' behavioral intention to adopt AI systems in public sector organizations.
H5: The managers' attitude toward AI systems' adoption positively influences their behavioral intention to adopt AI systems in public sector organizations.

Trust in AI Systems

Previous research has identified several factors that influence trust in AI and algorithms (Alexander et al., 2018; Shin, 2020, 2021). Among these, perceived fairness has been highlighted as a significant factor (Shin, 2020). While the concept of AI fairness is often discussed in the literature, there remains a lack of consensus on a definitive definition of fairness of AI algorithms (Shin & Park, 2019). However, there is an agreement that fairness is a critical element in designing and developing trustworthy AI systems (Hutchinson & Mitchell, 2019). The main goal of ensuring AI fairness is to prevent undesirable consequences. According to principles of AI ethics, fairness mandates that algorithmic decisions should avoid producing biased, discriminatory, or disproportionate impacts on individuals, communities, or specific groups throughout the AI system's lifecycle, from design and data collection to development, deployment, and usage (European Commission, 2019; OECD, 2019; SDAIA, 2023a; Shin & Park, 2019). Fairness is also recognized by the European Commission as a requirement for AI systems to be regarded as trustworthy (European Commission, 2019). Based on these considerations, we propose the following hypothesis:

H6: Perceived fairness positively influences public sector managers' trust in AI systems.

Humanity is also proposed as a fundamental principle of AI ethics, which calls for the ethical development of AI systems that are in harmony with essential human rights and cultural values, ensuring a beneficial impact on individuals and communities (European Commission, 2019; OECD, 2019; SDAIA, 2023a). Such systems should be designed to empower and augment human capabilities, not to deceive or control behavior (SDAIA, 2023a). The adoption of a human-centric design approach, which respects human agency and choice, is recommended (SDAIA, 2023a). In line with this principle, our study hypothesizes:

H7: Perceived humanity positively influences public sector managers' trust in AI systems.

The principles of reliability and safety are also cornerstones in the trustworthiness of AI systems (European Commission, 2019; OECD, 2019; SDAIA, 2023a). Reliability encompasses the assurance that AI systems will operate in strict accordance with their defined specifications, delivering consistent performance that matches the intentions of their creators. This reliability extends to the establishment of rigorous monitoring and control mechanisms that ensure ongoing alignment with the system's original design parameters and objectives (SDAIA, 2023a). Safety, in parallel, underscores the importance of developing AI systems that are free from potential hazards to both individuals and society (SDAIA, 2023a). It involves the proactive integration of safeguards within AI systems to avoid any possible damage and the preemptive measures against the misuse or malevolent exploitation of data that could lead to harm (SDAIA, 2023a). Incorporating these principles, we theorize that the perceived reliability and safety of AI systems are foundational in reinforcing the confidence of public sector managers in these systems. Hence, we propose the following hypotheses:

H8: Perceived reliability positively influences public sector managers' trust in AI systems.
H9: Perceived safety positively influences public sector managers' trust in AI systems.

Transparency in AI systems, coupled with their explainability, is acknowledged as an essential attribute for building trust (European Commission, 2019; OECD, 2019; SDAIA, 2023a; Shin, 2020). It is imperative for individuals engaging with AI to not only be aware that they are interacting with such systems but also to comprehend the logic underpinning the AI's decisions (OECD, 2019; Shin & Park, 2019). This understanding is crucial, particularly in circumstances where the AI's decision-making process could have adverse implications (European Commission, 2019). It is posited that transparency is not solely about openness; it inherently includes the system's explainability—its ability to render its operations and outcomes understandable to stakeholders (SDAIA, 2023a), enabling them to appraise and, if necessary, contest these outcomes. The explainability aspect of transparency ensures that stakeholders are not passive recipients of AI decisions but are empowered with the information to understand and question the basis of AI-generated outcomes, especially in a professional setting like the workplace (OECD, 2019).

In essence, explainability is an extension of transparency, serving as the communicative bridge that conveys the "how" and "why" behind AI actions in a user-friendly manner (Ehsan & Riedl, 2019).

This is essential, given that the mere visibility into a system's processes without a comprehensible explanation would be insufficient for stakeholders to form a reasoned trust in the technology. A transparent AI system, therefore, is one that not only reveals its decision-making stages and underlying data but also provides clear, accessible explanations of its inner workings and rationales (SDAIA, 2023a). This dual aspect of transparency and explainability is what allows affected individuals and communities to fully grasp, and where necessary, challenge the AI's outcomes (OECD, 2019). With these considerations in mind, the following hypothesis is proposed:

H10: Perceived transparency positively influences public sector managers' trust in AI systems.

Perceived accountability is a fundamental factor that influences trust in AI algorithms (Shin, 2020). The principle of accountability in AI systems is essential to establishing trust within the frameworks of their development and deployment (European Commission, 2019). It is recognized that organizations and individuals involved in the AI lifecycle—designers, developers, operators—are expected to be held accountable for ensuring that these systems function correctly and in accordance with the values-based principles (OECD, 2019).

Accountability encompasses the ethical responsibility and potential liability of all parties engaged with AI technologies, specifically for decisions and actions that may lead to risks or adverse effects on individuals and communities (SDAIA, 2023a). It requires that there be clear human oversight, governance, policies, regulations, and management to mitigate potential harm and misuse of AI (Engbers, 2020; SDAIA, 2023a). The technology should operate without deceiving individuals or impinging upon their freedom of choice, and those who are responsible for the AI system should be identifiable and ready to take responsibility for any unintended consequences (SDAIA, 2023a). Furthermore, mechanisms such as auditability play a crucial role, particularly in critical applications of AI, to ensure responsibility and accountability for the outcomes of AI systems. These mechanisms should be complemented by adequate and accessible redress to ensure that any grievances can be appropriately addressed (European Commission, 2019). In light of this review of accountability, we hypothesize:

H11: Perceived accountability positively influences public sector managers' trust in AI systems.

In the context of AI systems, the principles of privacy and security are important (SDAIA, 2023a), requiring that AI systems be developed and operated with high regard for data confidentiality and protection against breaches (European Commission, 2019; OECD, 2019; SDAIA, 2023a). These requirements are crucial throughout the entire AI system lifecycle, ensuring that the privacy of collected data is respected and robust security measures are in place to prevent unauthorized access and data misuse (OECD, 2019). Privacy and security encompass the protection of data but also extend to the integrity and governance of data usage. AI systems must be equipped with effective mechanisms and controls for governing and monitoring their operations and outcomes (OECD, 2019; SDAIA, 2023a). This ensures adherence to established privacy and security protocols and allows for continuous awareness over the system's life span (SDAIA, 2023a).

In information system research, the importance of perceived privacy and security as determinants of user trust is well-established (Majrashi, 2022). Research across various sectors, such as internet banking, has consistently demonstrated the significant influence of both perceived privacy and perceived security on user trust (Chandio, 2011; Feizi & Ronaghi, 2010; Kim & Prabhakar, 2000; Yousafzai et al., 2010). In the context of AI-based technologies, similar concerns regarding security and privacy are prevalent and have been shown to impact users' trust in these systems. For instance, Majrashi (2022) identified perceived privacy and security as crucial predictors of trust in his study on the adoption of voice recognition technologies in workplaces. Reflecting upon these findings and aligning with the fundamental principles of privacy and security in AI ethics guidelines (European Commission, 2019; OECD, 2019; SDAIA, 2023a), we propose the following hypotheses:

H12: Perceived privacy positively influences public sector managers' trust in AI systems.
H13: Perceived security positively influences public sector managers' trust in AI systems.

Trust is widely recognized as a pivotal factor influencing users' adoption of various technologies (Bahmanziari et al., 2003). It is prominently featured in TAM (Wu et al., 2011). In the context of AI, trust is similarly acknowledged as a key predictor within models assessing human adoption of AI systems (Choudhury & Shamszare, 2023; Choung et al., 2023; Shin, 2020). Therefore, we assume that perceived trust plays a significant role in shaping public sector managers' attitudes and behavioral intentions toward adopting AI systems in their organizations. This assumption is grounded in the understanding that trust can significantly impact both the cognitive and behavioral aspects of technology adoption. Consequently, the following hypotheses are proposed:

H14: Perceived trust positively influences managers' attitudes toward the adoption of AI systems in public sector organizations.
H15: Perceived trust positively influences managers' behavioral intentions to adopt AI systems in public sector organizations.

Social/Subjective Norms

Social or subjective norms refers to the perceived social pressure to engage or not engage in a certain behavior (Ajzen, 1991). It plays a critical role in shaping intentions and behaviors within the framework of various models. As Simon (2007) underscores, the impact of subjective norms on the predictability of models has been well-established (Hartwick & Barki, 1994; Mathieson, 1991; Venkatesh & Davis, 2000). In addition, both Majrashi (2022) and Simon (2007) have identified subjective norms as a significant factor influencing the adoption of voice recognition systems, a subset of AI technologies. For the context of this study, the author has incorporated subjective norms as a key construct within the research model to explore its influence on public sector managers' behavioral intention to adopt AI systems. Consequently, we propose the following hypothesis:

H16: Social/subjective norms positively influences managers' behavioral intention to adopt AI systems in public sector organizations.

Perceived Tolerance

Perceived tolerance within an organization encompasses the organization's openness to acknowledge and learn from failures as part of the innovation process (Slutzky, 2012). This concept extends to appreciating the value of calculated risk-taking and understanding that failures are often a precursor to significant advancements and successful adoption of new practices and technologies (Farson & Keyes, 2003; Slutzky, 2012). An organizational culture that tolerates failure recognizes that not every initiative will result in immediate success and that some degree of trial and error is essential for growth and discovery (Farson & Keyes, 2003). Such an environment is likely to encourage creative and fearless behaviors, which are crucial for fostering an innovative mindset (Kriegesmann et al., 2005). This perspective is especially relevant in the adoption of AI systems, where the learning derived from initial failures can significantly contribute to the refinement and successful integration of these technologies. Therefore, it stands to reason that an organization's perceived tolerance for failure is likely to impact managers' behavioral intentions toward adopting AI systems. Managers in organizations that support a culture of calculated risk-taking and learning from failures may be more motivated to proceed with the adoption of AI systems. Hence, the following hypothesis is proposed:

H17: The organization's perceived tolerance positively influences managers' behavioral intention to adopt AI systems in public sector organizations.

Perceived Impact

The perceived impact of technology adoption can be a critical determinant in forecasting the uptake of a particular technology (Niehm et al., 2010). However, in the domain of AI system adoption, there is a lack of research exploring how perceived impact affects adoption decisions. AI systems promise to deliver a range of benefits, extending beyond advancements at an organization level to encompass significant social and environmental gains. Ethical frameworks advocate for AI to reinforce societal and environmental well-being, ensuring alignment with sustainability objectives and the broader good (European Commission, 2019; SDAIA, 2023a). Economically, AI is posited to significantly increase annual growth rates, presenting transformative potential for both the public and private sectors (Purdy & Daugherty, 2016; Wirtz et al., 2019). In public sector contexts, AI adoption can be linked not just to achieving strategic organizational objectives but also to catalyzing improvements in public sector efficacy and driving socio-economic progression. Acknowledging the potential of perceived impact to serve as a primary predictor of managers' attitude and behavioral intention toward AI system adoption in public sector organizations, this variable has been included in our research model. Thus, we articulate the following hypotheses:

H18: The perceived impact positively influences managers' attitude toward adopting AI systems in public sector organizations.
H19: The perceived impact positively influences managers' behavioral intention to adopt AI systems in public sector organizations.

Isomorphic Pressure

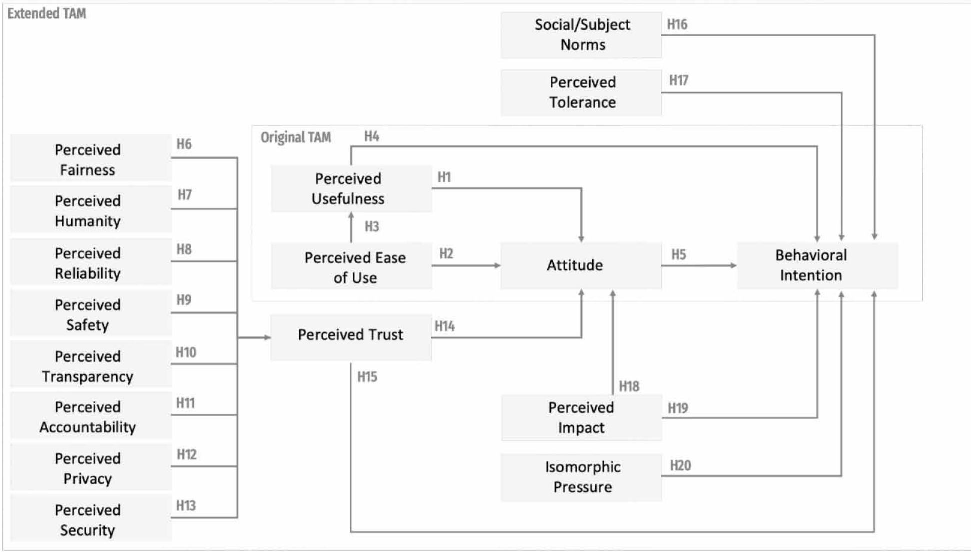
Institutional theory suggests that organizations encounter isomorphic pressures, which are influential forces driving them to emulate other entities within the same environmental context (DiMaggio & Powell, 1983; Hawley, 1968). DiMaggio and Powell (1983) identified three types of isomorphic pressures that can lead to changes within organizations: coercive, mimetic, and normative. Coercive pressures come from external sources, such as government or influential organizations, which force an organization to conform to certain practices or systems. Mimetic pressures arise when organizations opt to replicate the successful strategies or systems of their counterparts. Normative pressures are linked to the professionalization process within an organization, which steers organizational change to align with professional standards. Given the significance of these pressures, isomorphic pressure has been incorporated as a construct in the research model. The author hypothesizes that:

H20: Isomorphic pressure positively influences managers' behavioral intention to adopt AI systems in public sector organizations.

AI Adoption Model for Public Sector Managers (AI-AMPM)

The proposed AI adoption model for public sector managers (AI-AMPM) seeks to extend the TAM by incorporating additional factors crucial for understanding AI adoption in the public sector. This extension includes AI ethics and socio-organizational factors, which are vital for capturing the broader array of influences on AI adoption decisions made by public sector managers. As depicted in Figure 1, the AI-AMPM framework integrates these new dimensions into the traditional TAM structure,

Figure 1. Proposed AI Adoption Model for Public Sector Managers (AI-AMPM)



offering a more comprehensive view of the determinants of public sector managers' intentions to adopt AI in their workplaces.

METHODOLOGY

This section presents the methodology of the study, including the design and validation of the survey instrument and the composition of the sample.

The survey instrument employed in this study contained 62 items, utilizing a 5-point Likert scale that spanned from 1 "strongly disagree" to 5 "strongly agree," Some items were derived from previously validated measures, while others were newly developed in accordance with AI ethics principles, guidelines, and theoretical insights from relevant literature. The constructs of usefulness, ease of use, attitude, and behavioral intention were grounded in the technology acceptance literature (Al-Gahtani et al., 2007; Majrashi, 2022; Simon, 2007).

Items pertaining to fairness, humanity, reliability, safety, and transparency were developed based on AI ethics guidelines (European Commission, 2019; OECD, 2019; SDAIA, 2023a). Similarly, the accountability items were primarily sourced from these guidelines (European Commission, 2019; OECD, 2019; SDAIA, 2023a), with some elements adapted from related research (Engbers, 2020). Privacy, security, trust, and social norms items were primarily taken from the work of Majrashi (2022), with additional privacy and security items developed to align with AI ethics principles related to these factors (European Commission, 2019; OECD, 2019; SDAIA, 2023a). Items measuring tolerance were modified from Slutzky's research (Slutzky, 2012), and the perceived impact of adoption was formulated according to AI ethics guidelines (European Commission, 2019; SDAIA, 2023a) and synthesized based on relevant scholarly perspectives (Niehm et al., 2010; Purdy & Daugherty, 2016; Wirtz et al., 2019). Lastly, the construct of isomorphic pressures was constructed from DiMaggio and Powell's exposition of the three distinct types of isomorphic pressures (DiMaggio & Powell, 1983).

To ascertain the content validity of the survey instrument, expert reviews were employed, which is a common technique used for this purpose (Willis et al., 1999). Therefore, the instrument underwent evaluation by two academics with expertise in computer science, specifically in the field of AI, and an AI specialist from the software industry. They assessed the instrument from various aspects, such as the relevance of determinates, the appropriateness of items to each construct, the ordering of items, and potential redundancy or overlap among items. Following their comprehensive feedback, 10 items were eliminated due to issues with clarity, relevance, or redundancy, resulting in a refined instrument comprising 62 items rather than the initial 72.

An online questionnaire was circulated from August to October 2023 through several social networking platforms, including LinkedIn, Telegram, and WhatsApp. It specifically targeted public sector managers working in various Saudi government sectors known for their successful adoption of emerging technologies. These sectors included justice, health, culture, transport and logistics services, information technology and communications, tourism, education, public finance, industry and mining, environment, water, and agriculture, as identified by the Saudi Digital Government Authority (DGA, 2023).

The questionnaire resulted in 500 responses. After excluding 150 incomplete and 20 random responses, a total of 330 valid responses were retained, representing a completion rate of 66%. The demographic breakdown of our sample is as follows. Males constituted 78.5% and females 21.5%. In terms of age distribution, 26.4% of participants were aged 20-29, 44.2% were in their 30s, 22.1% in their 40s, and 7.3% in their 50s. The participants were all Saudi and working in the public sector in Saudi Arabia. Regarding the highest education levels, 7.3% of respondents had a diploma, 42.7% had a bachelor's degree, 40% had a master's degree, and 10% had a PhD. The respondents' managerial levels were 18.2% low-level, 57.9% middle-level, and 23.9% top-level. Participants with an IT-related specialization made up 32.4% of the sample, while those with non-IT specializations comprised 67.6%.

The Cronbach alpha test was used to evaluate the validity and internal consistency of the survey items for each construct. The outcomes indicated that the Cronbach's alpha value for each construct exceeded the acceptable threshold of 0.7 as recommended by Cronbach (1951), confirming the internal consistency of the instrument.

RESULTS AND DISCUSSIONS

Descriptive Results

The mean results (Table 1) reveal a varied range of responses regarding the determinants in the model. The average scores for the constructs provide insights into the participants' perceptions: notably high means for perceived usefulness and attitude toward AI adoption, at 3.73 and 3.80 respectively, suggest a favorable view of AI's benefits and a positive disposition toward its implementation. The mean for behavioral intention is also high at 3.71, indicating a strong inclination among public sector managers in Saudi Arabia to adopt AI systems. The mean score for perceived ease of use is at 3.36, showing managers' expectations regarding the user-friendliness of AI systems.

The perceived fairness, perceived humanity, perceived reliability, perceived safety, perceived transparency, perceived accountability, perceived privacy, and perceived security have means ranging from 2.44 to 2.89, suggesting potential concerns that could hinder the AI adoption process. The perceived trust, with a mean score of 2.56, suggests a moderate level of trust in AI systems among managers.

The mean score for perceived impact stands at 3.73, indicating that managers anticipate a significant positive effect from the adoption of AI systems across organizational, public sector, environmental, economic, and social dimensions. Social/subjective norms have a mean score of 2.50, pointing to a moderate impact of perceived social pressures and expectations on managers' intentions to adopt AI systems in public sector organizations. Perceived tolerance shows a mean score of 2.37, which implies a somewhat lower concurrence with organizational acceptance of failure and risk-taking in the adoption of AI systems. Lastly, isomorphic pressure registers a mean

Table 1. Mean and Standard Deviation for Each Construct

Construct	No of items	Mean	SD
Perceived Usefulness (PU)	3	3.73	1.14
Perceived Ease of Use (PEOU)	3	3.36	1.32
Perceived Fairness (PF)	3	2.82	1.46
Perceived Humanity (PH)	3	2.89	1.41
Perceived Reliability (PR)	3	2.70	1.45
Perceived Safety (PSAF)	3	2.48	1.38
Perceived Transparency (PTRA)	3	2.52	1.31
Perceived Accountability (PACC)	6	2.70	1.21
Perceived Privacy (PP)	5	2.44	1.22
Perceived Security (PSEC)	5	2.45	1.19
Perceived Trust (PTRU)	4	2.56	1.22
Social/Subjective Norms (SN)	3	2.50	1.31
Perceived Tolerance (PTOL)	4	2.37	0.94
Perceived Impact (PI)	5	3.73	1.12
Isomorphic Pressure (IP)	3	3.48	1.41
Attitude (AT)	3	3.80	1.28
Behavioral intention (BI)	3	3.71	1.34

Note. Sample, $n = 330$

score of 3.48, denoting substantial external influences that may shape public sector managers' decisions to adopt AI systems.

Correlation Results

To accurately assess the relationship between the variables, the Pearson correlation coefficient (r) was utilized. This statistical tool measures both the direction and strength of the relationships among the variables under study (Pallant, 2020). The value of the correlation coefficient (r) can be interpreted as follows: a range from 0.10 to 0.29 indicates a weak relationship, from 0.30 to 0.49 signifies a moderate relationship, and from 0.50 to 1.0 denotes a strong relationship (Cohen, 2013).

The correlation matrix (Table 2) reveals several notable relationships among the study variables. Perceived usefulness (PU) is strongly correlated with perceived impact (PI) at 0.824, indicating that the more useful the managers perceive the AI system, the greater the impact they perceive it to have. Similarly, attitude (AT) and behavioral intention (BI) are highly correlated at 0.910, suggesting that positive attitudes toward the AI system are closely linked to the intention to adopt it. Noteworthy is the strong correlation between perceived ease of use (PEOU) and isomorphic pressure (IP) at 0.775, suggesting that the ease with which managers perceive the AI systems may significantly influence the coercive, mimetic, and normative pressures of conformity within a group or industry.

Perceived fairness (PF) and perceived humanity (PH) exhibit a very strong correlation of 0.809, implying that the fairness perceived by managers in an AI system is closely associated with how humane they consider the system to be. Furthermore, the matrix demonstrates a robust correlation between perceived transparency (PTRA) and perceived security (PSEC) at 0.830, suggesting that

Table 2. Correlation Matrix

	PU	PEOU	PF	PH	PR	PSAF	PTRA	PACC	PP	PSEC	PTRU	SN	PTOL	PI	IP	AT	BI
PU	1																
PEOU	0.608**	1															
PF	0.380**	0.496**	1														
PH	0.376**	0.289**	0.809**	1													
PR	0.315**	0.412**	0.704**	0.718**	1												
PSAF	0.241**	0.384**	0.658**	0.635**	0.614**	1											
PTRA	0.293**	0.465**	0.750**	0.697**	0.732**	0.772**	1										
PACC	0.100	0.200**	0.542**	0.567**	0.527**	0.532**	0.661**	1									
PP	0.153**	0.360**	0.610**	0.566**	0.627**	0.702**	0.803**	0.649**	1								
PSEC	0.143**	0.390**	0.614**	0.574**	0.659**	0.694**	0.830**	0.669**	0.856**	1							
PTRU	0.192**	0.387**	0.515**	0.498**	0.675**	0.689**	0.761**	0.571**	0.724**	0.780**	1						
SN	0.159**	0.271**	0.347**	0.225**	0.374**	0.487**	0.570**	0.422**	0.531**	0.563**	0.574**	1					
PTOL	0.283**	0.334**	0.502**	0.422**	0.555**	0.500**	0.656**	0.410**	0.535**	0.607**	0.596**	0.405**	1				
PI	0.824**	0.604**	0.381**	0.365**	0.305**	0.210**	0.259**	0.134*	0.089	0.124*	0.204**	0.214**	0.248**	1			
IP	0.594**	0.775**	0.535**	0.500**	0.438**	0.555**	0.587**	0.356**	0.443**	0.453**	0.462**	0.302**	0.394**	0.580**	1		
AT	0.794**	0.539**	0.502**	0.547**	0.440**	0.398**	0.440**	0.216**	0.239**	0.241**	0.324**	0.238**	0.375**	0.799**	0.643**	1	
BI	0.788**	0.549**	0.521**	0.527**	0.419**	0.375**	0.447**	0.266**	0.249**	0.238**	0.316**	0.263**	0.366**	0.805**	0.636**	0.910**	1

Note. ** Correlation is significant at the 0.01 level (2-tailed). * Correlation is significant at the 0.05 level (2-tailed).

as managers' perceptions of the transparency of an AI system increase, so do their perceptions of its security.

In the context of privacy and security, perceived privacy (PP) and perceived security (PSEC) exhibit a high correlation of 0.856. This underscores the notion that privacy and security are frequently interlinked in people's perceptions. Interestingly, while perceived accountability (PACC) shows significant correlations with other variables, its relationship with perceived usefulness (PU) is not significant. This could suggest that managers' perceptions of accountability may not substantially influence their views on the system's usefulness, and vice versa.

Hypotheses Testing Results

In our study, linear regression tests were utilized to evaluate the proposed hypotheses. The analyses investigated the relationships among the foundational constructs of TAM, namely perceived usefulness, perceived ease of use, and their impact on users' attitudes and behavioral intentions (see Table 3). The results revealed that perceived usefulness is a substantial predictor, explaining 63.0% of the variance in attitudes toward AI adoption. Perceived ease of use was also shown to predict 29.1% of the variance in attitudes, and its effect was significant.

When combined, perceived usefulness and perceived ease of use accounted for 63.5% of the variance in attitudes with a significant F-value, $F(2, 327) = 284.667$, $p < 0.001$, indicating strong predictive power. Perceived ease of use also emerged as a significant predictor of perceived usefulness, accounting for 37.0% of its variance. Perceived usefulness and users' attitudes were also found to be significant predictors of behavioral intention, explaining 62.0% and 82.8% of the variance, respectively. These findings provide support for hypotheses 1–5, affirming the relevance of the original TAM constructs in the context of AI system adoption among public sector managers.

The regression analyses further examined the effects of various factors related to ethics guidelines and principles for trustworthy AI on managers' trust in AI systems, as outlined in Table 3 (H6-H13). The findings indicate that perceived fairness is a notable determinant, accounting for 26.5% of the variance in trust. Perceived humanity also emerged as a significant predictor, explaining 24.8% of the variance in trust. Notably, perceived reliability and perceived safety have significant predictive power, with 45.6% and 47.4% of the variance in trust explained, respectively. Perceived transparency was also found to significantly predict trust, accounting for 57.9% of its variance. Perceived accountability also contributes a considerable amount, explaining 32.6% of the variance in trust. For the constructs of perceived privacy and perceived security, the results were similarly significant, with perceived privacy explaining 52.4% and perceived security 60.9% of the variance in trust, indicating their strong influence on managers' confidence in AI systems. These results offer strong empirical evidence in support of hypotheses 6 through 13, underscoring the critical roles that fairness, humanity, reliability, safety, transparency, accountability, privacy, and security play in enhancing trust in AI systems among public sector managers. Each of these constructs, as validated by the high R-squared values, has a significant impact on trust as demonstrated by the substantial proportions of variance they explain.

Regarding hypotheses H14 and H15, the analysis indicated that trust in AI systems significantly predicts both attitudes toward AI adoption and the behavioral intention to adopt such systems. Trust explains 10.5% of the variance in managers' attitudes, suggesting that a higher level of trust correlates with more favorable attitudes toward AI system adoption. Similarly, trust accounts for 10.0% of the variance in behavioral intention, implying its importance in driving managers' readiness to implement AI systems in the public sector. However, the relatively modest variances of 10.5% for attitudes and 10.0% for behavioral intentions, as explained by trust, indicate that while trust is a contributing determinant; other variables such as perceived usefulness play a more significant role in influencing managers' attitudes and intentions regarding AI adoption. Overall, hypotheses 14 and 15 are affirmed.

The data indicated that social norms are a modest but significant predictor of behavioral intention, explaining 6.9% of the variance. This level of influence suggests that the social environment and the perceptions of influential individuals exert a moderate impact on public sector managers'

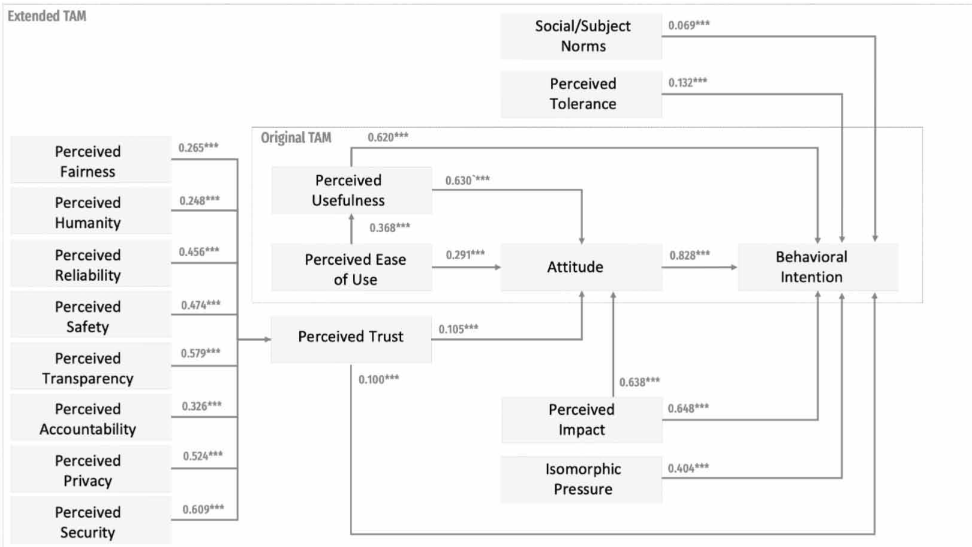
Table 3. Results of Hypotheses Testing

Hypothesis	Unstandardized Coefficients		Standardized Coefficients	*t*-value	Sig	F-value	Sig	R^2	Outcome
	β	SE							
H1: Usefulness → Attitude	0.888	0.038	0.794	23.639	< 0.001	558.824	< 0.001	0.630	Supported
H2: Ease of Use → Attitude	0.522	0.045	0.539	11.594	< 0.001	134.425	< 0.001	0.291	Supported
H3: Ease of Use → Usefulness	0.527	0.038	0.608	13.877	< 0.001	192.574	< 0.001	0.370	Supported
H4: Usefulness → Behavioral Intention	0.920	0.040	0.788	23.150	< 0.001	535.924	< 0.001	0.620	Supported
H5: Attitude → Behavioral Intention	0.950	0.024	0.910	39.688	< 0.001	1575.111	< 0.001	0.828	Supported
H6: Fairness → Trust	0.432	0.040	0.515	10.880	< 0.001	118.382	< 0.001	0.265	Supported
H7: Humanity → Trust	0.431	0.041	0.498	10.405	< 0.001	108.257	< 0.001	0.248	Supported
H8: Reliability → Trust	0.571	0.034	0.675	16.573	< 0.001	274.676	< 0.001	0.456	Supported
H9: Safety → Trust	0.609	0.035	0.689	17.201	< 0.001	295.866	< 0.001	0.474	Supported
H10: Transparency → Trust	0.709	0.033	0.761	21.228	< 0.001	450.639	< 0.001	0.579	Supported
H11: Accountability → Trust	0.576	0.046	0.571	12.595	< 0.001	158.630	< 0.001	0.326	Supported
H12: Privacy → Trust	0.726	0.038	0.724	18.984	< 0.001	360.389	< 0.001	0.524	Supported
H13: Security → Trust	0.800	0.035	0.780	22.609	< 0.001	511.177	< 0.001	0.609	Supported
H14: Trust → Attitude	0.340	0.055	0.324	6.205	< 0.001	38.500	< 0.001	0.105	Supported
H15: Trust → Behavioral Intention	0.346	0.057	0.316	6.029	< 0.001	36.345	< 0.001	0.100	Supported
H16: Social Norms → Behavioral Intention	0.268	0.054	0.263	4.933	< 0.001	24.335	< 0.001	0.069	Supported
H17: Tolerance → Behavioral Intention	0.518	0.073	0.366	7.131	< 0.001	50.846	< 0.001	0.134	Supported
H18: Impact → Attitude	0.909	0.038	0.799	24.027	< 0.001	577.292	< 0.001	0.638	Supported
H19: Impact → Behavioral Intention	0.957	0.039	0.805	24.580	< 0.001	604.193	< 0.001	0.648	Supported
H20: Isomorphic Pressure → Behavioral Intention	0.602	0.040	0.636	14.917	< 0.001	222.507	< 0.001	0.404	Supported

intentions to adopt AI systems. Despite the modest percentage, this finding still supports Hypothesis 16, underscoring the role of social norms in influencing behavioral intention. Similarly, tolerance was found to be a modest but more substantial predictor, accounting for 13.4% of the variance in behavioral intention. This percentage suggests that an organizational culture that embraces failure and supports risk-taking in the context of AI adoption can contribute to shape managers' intentions toward employing such technologies. This evidence supports Hypothesis 17, highlighting the importance of tolerance in the context of AI technology adoption.

The results revealed that perceived impact maintains a strong relationship with attitude, accounting for a significant 63.8% of the variance. This suggests that managers who acknowledge the positive effects of AI on their organization, the public sector, society, economy, and environment are inclined to hold favorable attitudes toward AI adoption. Perceived impact is also a major predictor of behavioral intention, explaining 64.8% of the variance. This indicates a close association between

Figure 2. AI Adoption Model for Public Sector Managers (AI-AMPM) With All Significant Relationships, ***p < .001



the recognition of AI's positive impacts and the intention to implement AI systems in public sector settings. Consequently, the findings provide robust support for both Hypotheses 18 and 19.

Isomorphic pressure demonstrates a significant predictive relationship with behavioral intention, explaining 40.4% of the variance. This substantial percentage suggests that external factors, including regulatory bodies' requirements and industry standards, play a considerable role in influencing public sector managers' intentions to adopt AI systems in their organizations. Therefore, the evidence strongly supports Hypothesis H20. Figure 2 shows the AI adoption model for public sector managers with all significant relationships.

Results of Multiple Regression Tests

The results in Table 2 indicated high correlations between the variables; hence, we assessed for multicollinearity. Multicollinearity refers to the presence of high intercorrelations among two or more independent variables within a multiple regression model. This phenomenon can be detected using the variance inflation factor (VIF) and tolerance metrics (Akinwande et al., 2015; Daoud, 2017). VIF analysis helps determine if a predictor variable has a strong linear relationship with other predictor(s). While there are no absolute rules for acceptable VIF values, it is commonly suggested that a VIF above 10 warrants concern (Akinwande et al., 2015; Myers & Myers, 1990). The tolerance statistic, being the reciprocal of VIF (1/VIF), also provides insight, with values below 0.1 indicating potential issues (Daoud, 2017). Upon conducting VIF analysis, it was determined that no predictor exhibited a VIF exceeding 10 nor a tolerance statistic below 0.1, as shown in Tables 4, 5, and 6. Therefore, it can be concluded that there is no multicollinearity among the variables, and no predictor has a strong linear relationship with any other predictor(s).

When combining fairness, humanity, reliability, safety, transparency, accountability, privacy, and security variables in a single block as predictors, the results showed they can account for 71.1% of the variance in trust, with $F(8, 321) = 98.724$, $p < 0.001$, suggesting that these factors together provide a strong predictive model for trust in AI systems among public sector managers (see Table 4). The high percentage of variance explained implies a substantial collective influence of these factors on the trust construct, reinforcing the idea of a multidimensional nature of trust in the context of AI adoption.

Table 4. Results of the Multiple Regression Test for Predicting Managerial Trust in AI Systems

Model Summary				
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**
1	.843	.711	.704	.667

ANOVA						
Model		**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
1	Regression	352.176	8	44.022	98.724	<.001
	Residual	143.136	321	.446		
	Total	495.312	329			

Coefficients[a]								
Model		**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**	**Collinearity Statistics**	
		β	**SE**	**Beta**			**Tolerance**	**VIF**
1	(Constant)	.479	.099		4.822	<.001		
	Perceived Fairness (PF)	-.159	.048	-.190	-3.298	.001	.271	3.685
	Perceived Humanity (PH)	-.112	.049	-.130	-2.299	.022	.282	3.541
	Perceived Reliability (PR)	.259	.042	.307	6.174	<.001	.365	2.741
	Perceived Safety (PSAF)	.200	.044	.226	4.538	<.001	.363	2.756
	Perceived Transparency (PTRA)	.232	.067	.249	3.461	<.001	.174	5.743
	Perceived Accountability (PACC)	.048	.044	.047	1.093	.275	.482	2.074
	Perceived Privacy (PP)	.041	.063	.041	.655	.513	.229	4.358
	Perceived Security (PSEC)	.348	.069	.339	5.049	<.001	.199	5.016

Note. [a] Dependent Variable: Perceived Trust (PTRU)

In addition, when combining usefulness, ease of use, trust, and impact as predictors, the results demonstrated that they can account for 72.1% of the variance in attitudes, with $F(4, 325) = 209.711$, $p < 0.001$ (see Table 5). This suggests that these elements collectively form a robust predictive model for managers' attitudes toward the adoption of AI systems in public sector organizations.

Furthermore, when usefulness, attitude, trust, social norms, tolerance, impact, and isomorphic pressure are combined as predictors, they explain a substantial 85.0% of the variance in behavioral intention, with $F(7, 322) = 261.612$, $p < 0.001$ (see Table 6). This high percentage of variance accounted for implies that these factors, when considered together, are significantly influential in shaping managers' behavioral intentions to adopt AI systems.

Table 5. Results of the Multiple Regression Test for Predicting Managerial Attitudes Toward the Adoption of AI Systems

<table>
<tr><th colspan="8">Model Summary</th></tr>
<tr><th colspan="3">Model</th><th>R</th><th>R Square</th><th colspan="2">Adjusted R Square</th><th>Std. Error of the Estimate</th></tr>
<tr><td colspan="3">1</td><td>.849</td><td>.721</td><td colspan="2">.717</td><td>.683</td></tr>
<tr><th colspan="8">ANOVA</th></tr>
<tr><th colspan="4">Model</th><th>Sum of Squares</th><th>df</th><th>Mean Square</th><th>F</th><th>Sig.</th></tr>
<tr><td colspan="2" rowspan="3">1</td><td colspan="2">Regression</td><td>392.253</td><td>4</td><td>98.063</td><td>209.711</td><td><.001</td></tr>
<tr><td colspan="2">Residual</td><td>151.974</td><td>325</td><td>.468</td><td></td><td></td></tr>
<tr><td colspan="2">Total</td><td>544.227</td><td>329</td><td></td><td></td><td></td></tr>
<tr><th colspan="9">Coefficients[a]</th></tr>
<tr><th colspan="2" rowspan="2">Model</th><th colspan="2">Unstandardized Coefficients</th><th>Standardized Coefficients</th><th rowspan="2">t</th><th rowspan="2">Sig.</th><th colspan="2">Collinearity Statistics</th></tr>
<tr><th>β</th><th>SE</th><th>Beta</th><th>Tolerance</th><th>VIF</th></tr>
<tr><td rowspan="5">1</td><td>(Constant)</td><td>-.159</td><td>.145</td><td></td><td>-1.098</td><td>.273</td><td></td><td></td></tr>
<tr><td>Perceived Usefulness (PU)</td><td>.481</td><td>.060</td><td>.430</td><td>8.049</td><td><.001</td><td>.301</td><td>3.317</td></tr>
<tr><td>Perceived Ease of Use (PEOU)</td><td>-.055</td><td>.039</td><td>-.057</td><td>-1.418</td><td>.157</td><td>.529</td><td>1.890</td></tr>
<tr><td>Perceived Trust (PTRU)</td><td>.181</td><td>.033</td><td>.173</td><td>5.437</td><td><.001</td><td>.848</td><td>1.180</td></tr>
<tr><td>Perceived Impact (PI)</td><td>.505</td><td>.060</td><td>.444</td><td>8.353</td><td><.001</td><td>.304</td><td>3.285</td></tr>
</table>

Note. [a] Dependent Variable: Attitude (AT)

CONCLUSION AND FUTURE WORKS

This study aimed to explore the determinants influencing public sector managers' intention to adopt AI systems in their organizations. Employing an extended TAM, we incorporated factors including fairness, humanity, reliability, safety, transparency, accountability, privacy, security, trust, social norms, tolerance, impact, and isomorphic pressure. Through an online survey, the author gathered and analyzed data from 330 public sector managers, using linear regression tests to evaluate the proposed model.

The findings revealed that several factors significantly influence managers' attitudes and behavioral intentions toward AI adoption. Notably, perceived usefulness and perceived impact emerged as strong predictors of both attitudes and behavioral intentions. Isomorphic pressure was also found as an important determinant in shaping public sector managers' behavioral intentions toward adopting AI systems in their organizations.

The study also highlighted the roles of perceived fairness, humanity, reliability, safety, transparency, accountability, privacy, and security in fostering trust of AI systems among public sector managers. Each of these factors significantly contributed to the variance in trust, with particularly high predictive power observed in perceived transparency, privacy, and security. These findings highlight the importance of adhering to ethical guidelines and principles for trustworthy AI in building

Table 6. Results of the Multiple Regression Test for Predicting Managerial Behavioral Intention Toward the Adoption of AI Systems

Model Summary				
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**
1	.922	.850	.847	.525

ANOVA						
Model		**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
1	Regression	504.902	7	72.129	261.612	<.001
	Residual	88.778	322	.276		
	Total	593.680	329			

Coefficients[a]								
Model		**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**	**Collinearity Statistics**	
		β	**SE**	**Beta**			**Tolerance**	**VIF**
1	(Constant)	-.340	.116		-2.921	.004		
	Perceived Usefulness (PU)	.101	.049	.086	2.034	.043	.259	3.857
	Attitude (AT)	.697	.044	.668	15.917	<.001	.264	3.788
	Perceived Trust (PTRU)	-.004	.035	-.004	-.120	.905	.459	2.80
	Social/Subjective Norms (SN)	.036	.027	.036	1.334	.183	.652	1.535
	Perceived Tolerance (PTOL)	.032	.039	.022	.807	.420	.597	1.674
	Perceived Impact (PI)	.195	.051	.164	3.0	<.001	.256	3.902
	Isomorphic Pressure (IP)	.040	.029	.042	1.349	.178	.482	2.076

Note. [a] Dependent Variable: Behavioral intention (BI)

confidence among public sector managers. The results also indicated that trust in AI systems plays a significant yet not exclusive role in shaping attitudes toward AI adoption and behavioral intentions to adopt such systems. This observation points to the multidimensional nature of AI system adoption, where trust is a key element but needs to be considered alongside other more influential factors such as perceived usefulness and perceived impact.

The focus on public sector managers in a specific geographic region (Saudi Arabia) may limit the generalizability of our findings. Therefore, future research should aim to diversify the sample by including public sector managers from different countries. Future studies might also explore the impact of demographic factors, such as age, education level, and gender, on managers' attitudes and behavioral intention toward AI adoption in public sector organizations. In addition, the dynamic nature of technology and organizational contexts means that our findings may evolve over time, warranting continuous research into the determinants of public sector managers' intention to adopt AI in workplaces.

This study contributed to the existing body of research on AI adoption in the public sector. It extended the TAM by integrating additional constructs related to AI ethics and socio-organizational factors, providing a more comprehensive framework for understanding AI adoption among public sector managers. It also empirically validated the influence of factors like perceived fairness, humanity, reliability, and transparency on trust of AI systems, contributing to the growing literature on trustworthy AI.

From a practical perspective, this study offers valuable insights to public sector entities, regulatory bodies, and AI system development firms. For public sector organizations and regulatory bodies, by employing the comprehensive framework presented in this study, they can undertake a thorough assessment of public managers' readiness for AI adoption. This process might involve identifying areas where managers may require additional awareness, training, or resources to be effectively encouraged to adopt AI technologies. For AI system development companies, the insights gained from our study can guide them in refining or developing their AI products and services to better meet the needs and expectations of public sector managers, potentially leading to more successful adoptions in public sector contexts.

COMPETING INTERESTS

The author of this publication declares there are no competing interests.

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Khalid Majrashi is an Associate Professor of computer science at the Digital Transformation and Information Center, Institute of Public Administration, Riyadh, Saudi Arabia. He received his Master's and Ph.D. degrees in Computer Science from RMIT University, Melbourne, Australia. His research interests include Human-Computer Interaction, and Human-centered AI.