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READY OR RESISTANT? EXAMINING SAUDI GOVERNMENT EMPLOYEE WILLINGNESS TO EMBRACE AI THROUGH THE UTAUT2 LENS

Mohamed G. Bendary, Vathana Bathmanath, Mohamad Khudari, Jegatheesan Rajadurai

College of Graduate Studies, Universiti Tenaga Nasional (UNITEN), 43000 Kajang, Selangor, Malaysia

Abstract: This research examines the adoption of AI technologies among Saudi government employees using an extended Unified Theory of Acceptance and Use of Technology (UTAUT2) framework. The adapted model includes variables such as performance expectancy, effort expectancy, social influence, facilitating conditions, price value, and personal innovativeness. Analysis of data from 117 respondents was conducted using Structural Equation Modeling (SEM) via SmartPLS 4.0. Contrary to traditional findings, results indicate that original UTAUT2 factors (performance expectancy, effort expectancy, social influence, and facilitating conditions) do not significantly influence AI adoption in this group. Instead, personal innovativeness stands out as a significant factor. This study enriches the public sector innovation literature by challenging existing UTAUT2 assumptions and underscoring the critical role of individual innovativeness in the uptake of AI technologies. Moreover, this research sets a foundation for further investigation into the effects of contextual and cultural nuances on technology adoption within the evolving landscape of AI.

Keywords: AI, Innovation, Saudi Arabia, Government, UTAUT2, Employees

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1 Introduction

The rapid advancement of artificial intelligence (AI) technologies has revolutionized multiple sectors, including healthcare (Alabbad et al., 2022; Alamoudi, 2022), finance (Bouteraa et al., 2024), energy (Duan et al., 2019), and education (Morgan et al., 2022), by enhancing decision-making, risk management, and customer interactions. Governments worldwide recognize AI's transformative potential in public services, aiming to improve decision-making processes, operational efficiency, and service delivery (Kurhayadi, 2022; Morgan et al., 2022; Sousa et al., 2019). AI applications in the public sector, such as automating routine tasks, fraud detection, and data analysis, demonstrate its capacity to enhance government programs and policies (Alhosani & Alhashmi, 2024; MANYIKA, 2017).

As one of the most crucial emerging technologies (Stevens & Zimmerman, 2021), AI is expected to contribute significantly to global economic growth, potentially adding $15.7 trillion to the world economy by 2030 (Kelly et al., 2023). Additionally, organizations utilizing AI with active human supervision can achieve cost savings of up to 30% and revenue increases of as much as 20% (Field et al., 2019). These statistics illustrate the substantial economic benefits of AI, reinforcing its importance in both the private and public sectors.

This global recognition of AI's benefits has led many countries to actively pursue its integration into their national strategies. For instance, Countries like Singapore, China, the United States, Argentina, Mexico, and the UAE have already integrated AI into key sectors such as healthcare, transportation, and education, showcasing AI's extensive potential to drive national development and digital governance (Almesafri & Habes, 2023; Bosque et al., 2014; Brynjolfsson & Mitchell, 2017; Buchanan, 2005).

Similarly, in Saudi Arabia, AI is a central component of the Vision 2030 initiative, which aims to transform the public sector through digital innovation. The Saudi government has allocated $1.6 billion to enhance digital infrastructure and aims to increase its digital economy by 50% (Alghamdi et al., 2023). As the largest spender on Information and Communications Technology (ICT) in the Middle East, Turkey, and Africa, Saudi Arabia is also one of the three highest investors in AI in the Arab world (Cabral, 2023; Solaiman et al., 2024). This substantial investment is expected to yield significant economic benefits, potentially adding 1.1 percentage points to Saudi Arabia's economic growth rate and Gross Value Added (GVA) of approximately USD 215 billion (Ashehri, 2019).

Public sector innovation is vital for modernizing government operations, particularly through the integration of AI technologies. Innovation, in this context, refers to the implementation of new technologies, methods, or processes that significantly deviate from traditional practices to improve public services (Glor, 1997; OECD/Eurostat, 2018). These advancements often come with challenges but ultimately seek to enhance operational efficiency and citizen satisfaction. In Saudi Arabia, the strategic adoption of AI within government services presents a unique opportunity to drive this innovation, aligning with the nation’s Vision 2030 goals of enhancing digital governance and public service delivery.

Given the scale of investment and the importance of AI in the nation's transformation, understanding the factors that influence its adoption in the Saudi public sector becomes crucial. This study applies the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model, which integrates several key factors, such as performance expectancy, effort expectancy, social influence, facilitating conditions, and price value, to explain individuals' acceptance and use of technology (Venkatesh et al., 2012). This model has been widely used in technology adoption studies, making it an appropriate framework for examining the willingness of Saudi government employees to embrace AI technologies. Using UTAUT2, this research aims to identify and measure these factors' significance in the Saudi public sector context.

1.1 Problem Statement

Despite substantial investments in AI and its potential benefits, the Saudi public sector faces significant challenges in fully leveraging these technologies. Key barriers include security and privacy concerns, infrastructure limitations, high implementation costs, lack of standardization, and inadequate employee readiness (Bendary & Rajadurai, 2024). Wong et al. (2019) emphasize that successful technology adoption requires not only access to high-tech equipment but also comprehensive training programs. both of which are currently insufficient in the Saudi public sector.

In addition to these structural barriers, a recent survey by Kaspersky highlights the existing skills gap, revealing that 62% of Saudi employees feel they need better digital skills, and 65% fear job loss due to inadequate IT knowledge (Zawya, 2023). This digital skills gap and fears of job displacement significantly inhibit AI adoption. Furthermore, the hierarchical nature of government organizations, along with varying levels of digital literacy among employees, exacerbates resistance to new technologies (Alenezi et al., 2021).

The specific context of the Saudi public sector, particularly regarding employee perceptions and acceptance of AI, remains underexplored. This lack of understanding hinders the effective implementation of Saudi Arabia's Vision 2030, which emphasizes digital transformation and AI integration to enhance public service efficiency (Vision 2030, n.d.).

This study aims to address this gap by investigating the factors influencing AI adoption among Saudi public sector employees, using the UTAUT2 model as a framework. By identifying key barriers and facilitators, this research will offer valuable insights to support the strategic objectives of Vision 2030, ultimately fostering a more innovative and digitally proficient public sector.

1.2 Research Question

To what extent do factors such as performance expectancy, effort expectancy, social influence, facilitating conditions, price value, and personal innovativeness significantly influence Saudi government employees' willingness to embrace AI technologies?

1.3 *Significance of the Study*

This study fills a gap by examining AI adoption among Saudi government employees, a context that has received limited attention. Incorporating personal innovativeness into the UTAUT2 model offers new insights into the role of individual traits in AI acceptance. This refined model contributes to the theoretical literature by enhancing the understanding of technology acceptance in unique cultural and organizational contexts, such as Saudi Arabia's public sector.

By employing survey data and quantitative analysis, the research offers empirical evidence that can inform policymakers and administrators on developing targeted strategies to enhance AI adoption and address employee concerns. These insights are particularly valuable for achieving the objectives of Saudi Arabia's Vision 2030, which focuses on digital transformation and innovation to improve public service delivery.

2 Literature Review

The concept of artificial intelligence (AI), first introduced by John McCarthy in 1956, aims to develop machines capable of independently mimicking human cognition (Haenlein & Kaplan, 2019). Over the past two decades, significant advancements in processing power, storage capacity, and reduced computational costs have fueled growing interest in AI technologies (Haenlein & Kaplan, 2019). Both governments and businesses have begun leveraging these advancements in applications such as process automation, virtual agents, predictive analytics, resource management, and enhanced security through threat intelligence (Ojo et al., 2019; Wirtz et al., 2019). As a result, citizens now expect governments to offer more responsive and personalized services, while businesses use AI to improve decision-making, manage risks, and tailor customer interactions (Deranty & Corbin, 2024; Madan & Ashok, 2022).

2.1 *Overview of AI in the Government Sector*

While much research has focused on governments' regulatory role regarding AI (Kuziemski & Misuraca, 2020), there is growing recognition of its transformative potential within government operations. Experts recommend a strategic approach to AI adoption in the public sector, considering organizational, ethical, and societal impacts while acknowledging AI's ability to revolutionize service delivery (Alhosani & Alhashmi, 2024). AI can significantly enhance public services, improve decision-making, and enable proactive governance (Rama Padmaja & Lakshminarayana, 2024).

This transformative potential is not limited to developed nations. Aly (2022) emphasizes the value of AI in facilitating digital transformation in developing countries. The combination of AI and open government data can amplify efficiency, foster innovation, and even contribute to crime prevention in public governance (Tan, 2022).

Moreover, AI has proven to be an effective tool for IT managers in driving digital transformation, underscoring its practical utility in modernizing governmental functions (Lovis, 2019). As technology evolves, governments and businesses must educate their workforce to ensure that the benefits of AI are widely shared (Ghani et al., 2022). Furthermore, ethics-based auditing and robust governance mechanisms are necessary to mitigate the risks and harms associated with AI systems (Minkkinen et al., 2024). The integration of these innovations can enhance corporate governance, especially in light of the digital transformation accelerated by the COVID-19 pandemic (Ahmed, 2024). Given the complexity of these technologies, scholars agree that further research is needed to fully understand their implications and optimize their implementation (Vázquez Cintrón, 2022).

2.2 *Saudi Arabia's National AI Strategy and Initiatives*

The Kingdom of Saudi Arabia's Vision 2030 positions Artificial Intelligence (AI) as a cornerstone of national transformation, leveraging its potential to enhance services across multiple sectors (Rahman & Qattan, 2021; Vision 2030, n.d.). Tangible initiatives support this vision. In 2017, the National Digital Transformation Unit (NDU) was established to oversee the implementation of digital transformation efforts, ensuring their progress and performance (National Committee for Digital Transformation, 2017).

Building on this foundation, the Saudi Data & AI Authority (SDAIA) was formed in 2019, aligning its efforts with Vision 2030's objectives (Saudi Data and AI Authority, n.d.). SDAIA plays a central role in advancing Saudi Arabia's global leadership in AI through various initiatives. In 2020, SDAIA launched the National Strategy for Data and AI (NSDAI), which outlines a roadmap to position Saudi Arabia among the top 15 countries in AI and tenth in open data. The strategy emphasizes ethical and sustainable AI applications, reflecting the nation's commitment to responsible AI development (Saudi Data and AI Authority, 2020). Further, SDAIA published the Principles and Controls of AI Ethics in 2023, aligning with international standards to mitigate potential risks associated with AI systems (Saudi Data and AI Authority, 2023).

Under SDAIA's leadership, numerous transformative projects have been launched across the kingdom. For instance, the NEOM city project aspires to be a smart city powered by AI, with smart schools at its core (Alnasib, 2023). Likewise, the National Center for Robot Technology and Smart Systems within King Abdulaziz City for Science and Technology reflects Saudi Arabia's dedication to fostering AI in education (Alnasib, 2023).

In collaboration with the private sector, Saudi Arabia utilises AI for urban safety initiatives, such as employing computer vision to enforce seat belt usage and detect traffic violations. Advanced traffic cameras are also being developed to monitor dangerous driving behaviour through video analysis, contributing to an intelligent transportation system that supports better traffic management (Ashehri, 2019).

One notable symbol of Saudi Arabia's AI advancements is Sophia, the world's first robot citizen, who was granted Saudi citizenship during the 2017 Summit on Future Investment Initiative in Riyadh (Fernandes, 2022). This milestone underscores the Kingdom's leadership in AI innovation and its commitment to embracing cutting-edge technologies. Through these initiatives, Saudi Arabia seeks to meet the goals of Vision 2030 and solidify its position as a global leader in AI and digital innovation.

2.3 *The Unified Theory of Acceptance and Use of Technology (UTAUT2)*

The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), introduced in 2012, is an evolution of the original UTAUT model, offering a comprehensive framework to understand individuals' acceptance and use of technology (Venkatesh et al., 2012). This enhanced model integrates various acceptance and behavioural assessment frameworks, such as the Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), Theory of Reasoned Action (TRA), The Motivational Model, Model of PC Utilization, Innovation Diffusion Theory, and Social Cognitive Theory (Kessler & Martin, 2017; Venkatesh et al., 2012). UTAUT2 retains the four core constructs from the original UTAUT—performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC)—while adding constructs like hedonic motivation (HM), price value (PV), and habit (HT) to predict consumer behaviour better (Venkatesh et al., 2012; Venkatesh et al., 2016). Notably, the voluntariness of use, a moderator in the original model, is omitted in UTAUT2 to better align with consumer-focused contexts.

2.4 *UTATUT2 Adaptation*

UTAUT2 has gained widespread recognition for its adaptability, as demonstrated by its application across varied research domains. Its flexibility is highlighted through its use in studies ranging from mobile commerce (Kalinić et al., 2019) and e-government (Kalamatianou & Malamateniou, 2017; Munyoka & Maharaj, 2017; Syamsudin et al., 2018) to cutting-edge fields like augmented reality (AR) (Khashan et al., 2023), artificial intelligence (AI) (Almahri et al., 2020; Das & Datta, 2024; Mokmin & Ibrahim, 2021), the Internet of Things (IoT) (Shi et al., 2022; Zaky et al., 2020), and blockchain (Handoko et al., 2020; Hannoun et al., 2021; Sheel & Nath, 2020). Researchers have tailored UTAUT2 by introducing new constructs, such as trust (Gharaibeh et al., 2018; Kalinić et al., 2019; Zefreh et al., 2023) or risk perception (Hannoun et al., 2021; Khashan et al., 2023), particularly in contexts where security and privacy are critical, such as in blockchain and e-commerce.

On the other hand, the model excludes constructs that may be irrelevant or less impactful for certain technologies or settings. For instance, Das & Datta (2024) and Mokmin & Ibrahim (2021) excluded price value, while Alalwan et al. (2019) and Marriott & Williams (2018) excluded facilitating conditions. Similarly, Aswani et al. (2018) and Khashan et al. (2023) omitted habit, as it did not significantly affect the outcomes in their analyses.

Additionally, the model's flexibility extends to its moderator variables, broadening its applicability across different studies. While originally including age, gender, and experience as moderators (Venkatesh et al., 2012), researchers have incorporated or excluded moderators based on the specific needs of their studies. For instance, some studies have added location and language to account for geographic and linguistic factors (Munyoka & Maharaj, 2017), while others have removed moderators where their impact was minimal (Alalwan et al., 2019; Eneizan et al., 2019; Zefreh et al., 2023).

UTAUT2's versatility is evident across various research methodologies, including qualitative (Mezei et al., 2022; Schretzlmaier et al., 2022), quantitative (Dionika et al., 2020; Muhardi Saputra et al., 2021; Syamsudin et al., 2018), and mixed methods (Duarte & Pinho, 2019; Mokmin & Ibrahim, 2021) approaches. The framework supports qualitative insights and the empirical rigour of quantitative analysis, making it well-suited for mixed methods studies that benefit from both approaches.

Furthermore, UTAUT2's application is not limited by sector. It has been used to study technology acceptance in public and private sectors. For instance, it has been applied to research on fitness apps, mobile app stores (Alalwan et al., 2019), and online hotel bookings (Chang et al., 2019) in the private sector, as well as e-government service usage (Kalamatianou & Malamateniou, 2017; Muhardi Saputra et al., 2021; Munyoka & Maharaj, 2017; Syamsudin et al., 2018) and public Wi-Fi adoption (Aswani et al., 2018) in the public sector.

2.5 *Applications of UTAUT2 in Understanding AI Adoption Across Various Sectors*

UTAUT2 has been widely employed to explore factors influencing the willingness of users to adopt AI technologies. Bouteraa et al. (2024) utilized UTAUT2 to understand bankers' willingness to use ChatGPT, highlighting the model's applicability in finance. Similarly, Pande and Taeihagh (2024) examined user acceptance of autonomous systems, such as driverless cars, which operate with minimal human intervention, demonstrating the framework's relevance in studying emerging technologies. Wu et al. (2022) explored the factors influencing college students' willingness to use AI, emphasizing UTAUT2's effectiveness in educational settings.

In professional environments, Vázquez Cintrón (2022) investigated factors affecting AI adoption among IT managers during digital transformation processes in the United States, while X. Zhang & Wareewanich (2024) focused on teachers' willingness to use generative AI. Alneyadi et al. (2023) applied UTAUT2 to examine the determinants of user intention to adopt AI-based cybersecurity systems within the UAE government, further validating the model's robustness in a governmental context.

Moreover, UTAUT2 has been instrumental in understanding consumer behaviour in public services. Kuberkar and Singhal (2020) studied the adoption of AI-powered chatbots in Indian public transport services within a smart city framework. Likewise, studies examining the acceptance of AI-powered chatbots in government services further demonstrate UTAUT2's adaptability across different applications and contexts, including Kuberkar & Singhal (2020)'s research on Indian public transportation and Abbas et al. (2023)'s study of digital government in Norway.

In the public healthcare sector, W. Huang et al. (2024) explored patients' acceptance of AI and machine learning innovations at the National Heart Centre in Singapore, highlighting the model's utility in evaluating healthcare system efficiency and cost-effectiveness. These diverse applications underscore UTAUT2's relevance and adaptability in studying users' willingness to adopt AI technologies across various sectors.

Such widespread application of UTAUT2 demonstrates its capability to adapt to diverse technologies, user demographics, and cultural environments, making it a preferred model for researchers aiming to understand the complexities of technology adoption and usage across different sectors.

2.6 *Gap in Study*

While the UTAUT2 model has been widely applied in various technology adoption studies, its specific application to employees' willingness to embrace AI in the Saudi Arabian public sector remains underexplored. This gap is particularly significant given the potential for cultural, technological, and service-specific nuances within the Saudi context, which could significantly influence employee perceptions and acceptance of AI solutions. Moreover, existing research on AI adoption in governments is limited (Valle-Cruz et al., 2019; W. Zhang et al., 2021), and little is known about the specific factors influencing IT managers' decisions to adopt AI during digital transformations in the public sector (Vázquez Cintrón, 2022). This lack of knowledge hinders our understanding of promoting employee acceptance of AI and maximizing its benefits for Saudi government services.

Several key factors motivate a closer examination of UTAUT2 within the context of the Saudi public sector. First, emerging technologies such as AI often possess distinct features and user interactions compared to traditional technologies. These unique characteristics can influence user perceptions and adoption intentions in nuanced ways, necessitating a tailored UTAUT2 model to capture these specificities (Araullo & Potter, 2014; Fotaki et al., 2021).

Second, the cultural context of Saudi Arabia presents challenges to the generalizability of UTAUT2 findings across different regions. While extensive research has explored technology acceptance within public services, most studies have focused on regions outside of Saudi Arabia, including Zambia, Greece, Indonesia, and Turkey (Kalamatianou & Malamateniou, 2017; Korkmaz et al., 2021; Muhardi Saputra et al., 2021; Syamsudin et al., 2018).Furthermore, Migliore et al. (2022) found a significant moderating effect of culture on mobile payment adoption between China and Italy, underscoring the variability in the influence of UTAUT2 constructs across different cultural contexts. This finding highlights the need to critically examine cultural and geographic influences, particularly in a region with a distinct cultural landscape like Saudi Arabia (Alkhiri, 2022a, 2022b).

Third, the unique needs and challenges of the public sector in Saudi Arabia necessitate a re-examination of UTAUT2 constructs within this domain. Although UTAUT2 has been applied within the Saudi context (Abed et al., 2015; Alsheikh et al., 2022; Baabdullah et al., 2014, 2015; Barnawi et al., 2023; Zia & Alzahrani, 2022), most of these studies focused on sectors beyond public services, such as mobile banking, solar energy, and e-marketing. The public sector faces distinct challenges, including a shortage of readily available and competent personnel with the necessary AI skills (Duan et al., 2019). This calls for a sector-specific adaptation of the UTAUT2 model.

Finally, existing research on UTAUT2 reports inconsistencies in the strength and significance of relationships between core constructs and technology acceptance across various contexts (Aswani et al., 2018; Baabdullah et al., 2014; Dionika et al., 2020; Korkmaz et al., 2021; Migliore et al., 2022; Syamsudin et al., 2018). These inconsistencies necessitate a re-examination and contextualization of these relationships within the Saudi Arabian context, particularly with regard to emerging technologies such as AI.

By addressing this gap in knowledge, a more precise understanding can be developed regarding how the factors outlined by the UTAUT2 model influence employees' willingness to embrace AI solutions in the Saudi public sector. This understanding will ultimately guide the development and implementation of AI solutions that contribute to achieving the objectives of Vision 2030. Furthermore, this research will provide valuable insights into AI governance and public administration, with a specific focus on the Saudi context.

2.7 *Hypothesis*

The formulation of hypotheses is a critical step in scientific research, guiding the investigation and interpretation of results (Sekaran & Bougie, 2016). Once the research variables have been identified and the relationships among them established through logical reasoning within the theoretical framework, researchers are poised to test whether the theorized relationships hold true (Sekaran & Bougie, 2016).

2.7.1 Performance Expectancy (PE)

As outlined by Venkatesh et al. (2012), performance Expectancy is defined as the degree to which consumers believe that using a technology will benefit them in performing specific activities, marking it as a fundamental element in the technology adoption process. Within this research context, PE refers to Saudi government employees' belief that AI will enhance their productivity and enable them to deliver more efficient public services. This belief is critical, forming the basis for the assumption that government employees are likely to adopt technologies they perceive as advantageous.

The pivotal role of PE in influencing users' behavioural intentions towards technology adoption is supported by a body of research, including studies by Sheel & Nath (2020) and Venkatesh et al. (2012), which emphasize its essential role in the decision-making process concerning technology engagement. This impact is further evidenced in the realm of customer experience and satisfaction, with contributions from Bataineh (2022), Gupta et al. (2023), Kalinić et al. (2019), Li et al. (2024), and Rombaut et al. (2020) demonstrating PE's significant positive influence. Additionally, the relevance of PE in the domain of e-government services is supported by findings from Kalamatianou & Malamateniou (2017), Munyoka & Maharaj (2017), and Syamsudin et al. (2018), showcasing its broad applicability across various technological interventions.

The dynamics between PE and the intention to adopt technology have been thoroughly examined across studies focusing on emerging technologies like Artificial Intelligence (AI), the Internet of Things (IoT), Blockchain, Augmented Reality (AR), and Autonomous technologies. Significant insights from Almahri et al. (2020), Das & Datta (2024), Kessler & Martin (2017), Mokmin & Ibrahim (2021), Shi et al. (2022), Zaky et al. (2020), Hannoun et al. (2021), Khashan et al. (2023), and Zefreh et al. (2023) collectively affirm PE's crucial role in shaping users' technology usage intentions, especially within the context of emerging technologies.

However, the impact of PE can vary significantly across different cultural contexts. In collectivist cultures, the collective benefits of technology might be more influential than individual productivity gains. For example, a study by Syamsudin et al. (2018) in Indonesia found that PE did not significantly influence the intention to use e-government services, suggesting that other factors like social influence or facilitating conditions might play a more critical role in such contexts. Considering these factors, this research proposes:

Hypothesis 1 (H1): Performance expectancy, encompassing both perceived improvements in employee productivity and the ability to deliver more efficient public services, positively influences Saudi government employees' willingness to embrace AI.

2.7.2 Effort Expectancy (EE)

Effort Expectancy, as defined by Venkatesh et al. (2012), refers to the perceived ease of using a technology. EE reflects the consumer's consideration of time and effort in forming an overall view of the effort required for accepting and using a technology. This evaluation process involves a cognitive trade-off, where consumers weigh the extent of ease against the perceived benefits of using new technology, as Davis (1989) suggested. In this study, EE reflects Saudi government employees' perception of the effort involved in learning and using AI in their daily work.

Research findings have consistently underscored Effort Expectancy's substantial positive impact on the behavioural intention toward adopting digital public services, underscoring its pivotal role in technology adoption across various digital platforms. This assertion is supported by studies such as Dionika et al. (2020), which affirm EE's influence on digital public services, alongside evidence from Munyoka & Maharaj (2017), Syamsudin et al. (2018), and Baabdullah et al. (2014) that extends its significance to e-government service usage and mobile services.

Given these considerations, this research posits the following hypothesis:

Hypothesis 2 (H2): Effort expectancy influences the willingness of Saudi government employees to embrace AI positively and significantly.

2.7.3 Social Influence (SI)

As defined by Venkatesh et al. (2012), social influence captures how an individual's decision to adopt a technology is swayed by the opinions or recommendations of their social circle. In this context, SI examines how endorsements from a government employee's colleagues or superiors might influence their willingness to embrace AI.

While the role of Social Influence in technology adoption has been omitted in certain studies, such as those by Alalwan et al. (2019) and Bataineh (2022), its critical importance across diverse technological contexts remains evident. Empirical research has highlighted SI's significant impact on the acceptance and use of technologies, including the adoption of Government Resource Planning (GRP) systems among Indonesian citizens (Muhardi Saputra et al., 2021), the utilization of public WiFi in India (Aswani et al., 2018), and the embrace of autonomous vehicles in developing countries, including Saudi Arabia (Zefreh et al., 2023). These examples illustrate the profound influence of social networks and perceived social pressure on shaping technology adoption behaviours.

However, the influence of Social Influence exhibits notable inconsistencies, particularly when comparing potential adopters to post-adopters, as identified by Yang (2012). This variability is further demonstrated in the context of mobile payment adoption. In China, Chen et al. (2019) found that SI had no significant impact on adoption intention, a finding echoed by Migliore et al. (2022) in their study of mobile payment adoption in Italy and China. Their research revealed a stark contrast between the two countries, with Italian respondents showing a positive and significant response to SI, while Chinese respondents experienced a negative and non-significant effect, indicating significant divergence in SI's influence across cultural contexts. Additionally, Zhou et al. (2021) reported that SI does not significantly affect the intention to use e-commerce, further underscoring social factors' complex and varied effects on technology adoption intentions. Given these considerations, this research posits the following hypothesis:

Hypothesis 3 (H3): Social influence positively and significantly influences the willingness of Saudi government employees to embrace AI.

2.7.4 Facilitating Conditions (FC)

Facilitating conditions, a core construct in the UTAUT model (Venkatesh et al., 2012), represent a user's perception of the resources and support available to adopt a technology. In this context, FC examines how Saudi government employees perceive the availability of infrastructure, technical support, and other resources needed to embrace AI technologies effectively. The construct reflects the extent to which employees believe that an adequate environment, both in terms of technology and support, is in place to facilitate their interaction with AI technologies, thereby influencing their intention to use them (Venkatesh et al., 2012).

The impact of Facilitating Conditions on technology adoption has been affirmed across a range of technological fields, from Augmented Reality (AR), as demonstrated by (Khashan et al., 2023), to AI, discussed by Das & Datta (2024), to Blockchain technology, explored by Hannoun et al. (2021). This evidence underscores FC's role in fostering technology acceptance by ensuring users have the necessary resources and support.

However, the relevance of FC has not been uniformly recognized across all studies. Specifically, some research has overlooked FC's contribution to technology acceptance (Alalwan et al., 2019; Marriott & Williams, 2018; Pramudita et al., 2023). Additionally, other studies have directly questioned its significance. For instance, Syamsudin et al. (2018) found FC to lack a meaningful impact on the intention to use e-government Services, paralleling findings by Migliore et al. (2022) regarding mobile payment adoption in Italy. Similarly, Korkmaz et al. (2021) observed that FC did not significantly influence the behavioural intention to use autonomous public transport systems in Turkey. Additionally, research by Baabdullah et al. (2014) highlighted FC's limited effect on the adoption of M-Government services in Saudi Arabia.

Hypothesis 4 (H4): Facilitating conditions positively and significantly influence the willingness of Saudi government employees to embrace AI.

2.7.5 Price Value (PV)

Price Value is the perceived balance between the expenses and advantages of utilizing a new system or technology (Zhou et al., 2021). This aligns with the UTAUT2 construct defined by (Venkatesh et al., 2012, 2016) as the perceived trade-off between a technology's benefits and its costs. Traditionally, PV is crucial in consumer settings where financial considerations heavily influence adoption decisions (Wang & Zhang, 2023). However, in the context of government technology adoption, the concept of PV might extend beyond direct financial costs. It could encompass factors like resource allocation, training requirements (Digital Government Authority, 2021a, 2021b), and potential maintenance expenses (Ministry of Municipal and Rural Affairs and Housing, 2022).

Furthermore, price is a fundamental component of value perception (Kessler & Martin, 2017), influencing consumers' decisions about whether a product or service is worth its cost. For instance, PV has significantly predicted behavioural intention in technology adoption contexts such as autonomous vehicles (Liang et al., 2020) and digital payment systems (Gupta et al., 2023). It also positively influences customer satisfaction in mobile commerce services (Kalinić et al., 2019) and live-streaming shopping (Sun, 2023). Understanding the perceived value of AI in relation to its associated costs is crucial for predicting employee acceptance in the public sector.

Given this broader interpretation, the following hypothesis is proposed:

Hypothesis 5 (H5): Price Value influences the willingness of Saudi government employees to embrace AI positively and significantly.

2.7.6 Additional Constructs

This study enhances the established UTAUT2 framework by incorporating additional constructs to deepen the understanding of AI adoption dynamics within the Saudi public sector. The following section outlines how these new elements contribute to the model, providing insights into the factors that influence government employees' adoption of innovative technologies.

2.7.6.1 Personal Innovativeness (PI)

Innovativeness is a key personality construct that reflects an individual's willingness to embrace new products or ideas offering novel experiences (Marriott & Williams, 2018). This trait, as Lu et al. (2005) define, manifests as the readiness of a person to experiment with new technologies, fundamentally influencing their approach towards adopting and integrating these innovations into their daily lives. T.-L. Huang & Liao (2015) highlight that individuals with lower levels of cognitive innovativeness tend to prioritize the effort or ease of use and the "playfulness" of technology, underscoring the diverse impact of innovativeness on technology interaction. Moreover, the degree of innovativeness not only affects the frequency of use but also the sustainability of the user's engagement with interactive technologies (Kessler & Martin, 2017).

Furthermore, studies within the Saudi context provide mixed results regarding the influence of innovativeness on technology adoption. Baabdullah et al. (2016) examined the impact of innovativeness on consumer adoption of mobile government services in Saudi Arabia and found a significant positive influence. Similarly, Badwelan et al. (2016) investigated factors affecting user intention to adopt M-learning and concluded that personal innovativeness significantly influences the behavioral intention to use M-learning. However, Asif & Fazel (2024) found personal innovativeness in technology to be insignificant when examining factors influencing tourists' adoption of technology for destination information searches in Saudi Arabia.

This inconsistency highlights the potential dependence of innovativeness's effect on the specific technology in question. Given the novelty and transformative potential of AI, it is reasonable to expect a different influence compared to mobile government services or M-learning. Supporting this notion, Alshaafee et al. (2021) also found a significant positive influence of personal innovativeness on the adoption of smart cars, a technology with some parallels to AI. Therefore, investigating the impact of innovativeness on Saudi government employees' willingness to embrace AI is particularly relevant and can contribute to understanding the adoption process in this specific context.

Hypothesis 6 (H6): User innovativeness significantly and positively influences the willingness of Saudi government employees to embrace AI.

2.7.7 Eliminated Constructs

2.7.7.1 Habit

Habit refers to behaviors performed automatically due to learning (Venkatesh et al., 2016). However, evidence from the public sector suggests its impact on behavioral intention and actual usage might be less pronounced. For instance, studies in Indonesia (Dionika et al., 2020; Muhardi Saputra et al., 2021) investigating habit's role in adopting government services found minimal impact. Additionally, the novelty of AI technology (Sheel & Nath, 2020; Zefreh et al., 2023) makes habit formation less likely in the timeframe of this study. Finally, the inherent difficulty of measuring habit as an unobservable psychological construct (Hoo et al., 2019) and the ongoing challenges in operationalizing and quantifying it (Nilsen et al., 2012) further support excluding habit from this research framework.

2.7.7.2 Hedonic Motivations

Hedonic motivation, as defined by Venkatesh et al. (2012), refers to the enjoyment and pleasure users derive from interacting with technology. While intrinsic motivation plays a more prominent role in customer-oriented contexts, particularly with technologies designed for hedonic use (Brown & Venkatesh, 2005; van der Heijden, 2004), its influence appears limited in the public sector. Studies examining government employee acceptance of technology in similar contexts, such as digital payment systems among Jordanian government employees (Al-Okaily et al., 2020) and information technology adoption among Yogyakarta Region government employees (Syaifuddin et al., 2022), have excluded hedonic motivation as a relevant factor. Moreover, research conducted in diverse settings, including Indonesia (Dionika et al., 2020; Syamsudin et al., 2018), Turkey (Korkmaz et al., 2021), and Saudi Arabia (Baabdullah et al., 2014), demonstrates that hedonic motivation does not significantly affect the adoption of technologies like e-government, autonomous public transport systems, and mobile government services. Thus, the variable's removal is consistent with findings that its impact is negligible in public sector contexts.

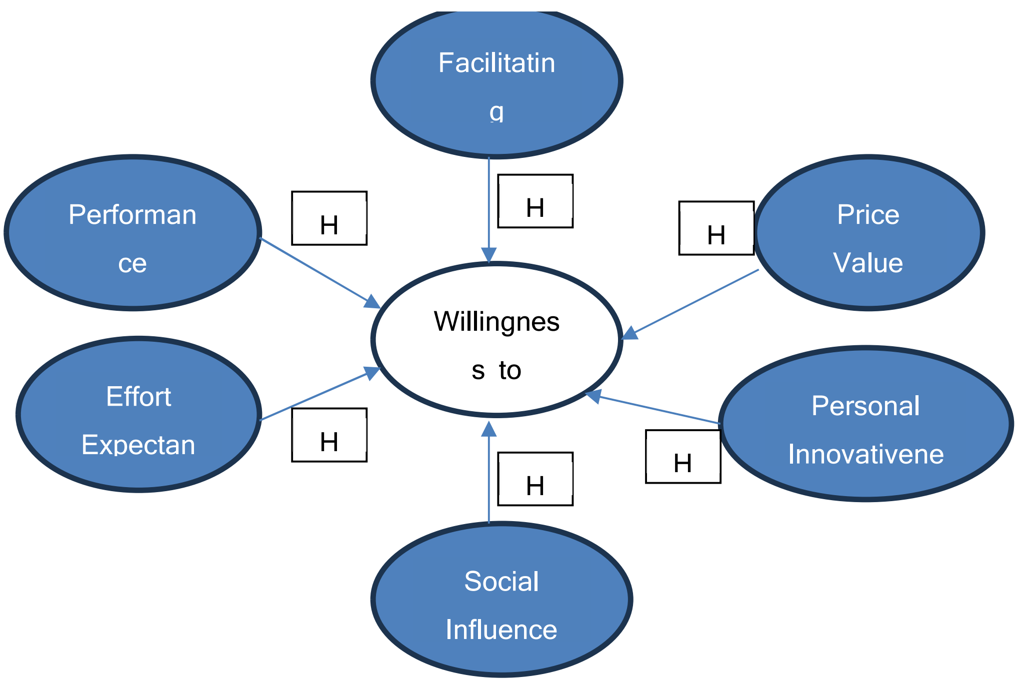
2.7.7.3 Use behaviour

The UTAUT2 model, designed to capture the nuances of user behaviour across different technologies (Venkatesh et al., 2016), includes a construct for actual behaviour. This construct traditionally measures how often users engage with technology and is used to predict continued use (Venkatesh et al., 2016). However, as this study focuses on understanding the willingness of Saudi government employees to adopt AI, this study will exclude the actual behaviour construct, aligning with research by N. Huang et al. (2021), Kuberkar & Singhal (2020), Patil & Undale (2023), and X. Zhang & Wareewanich (2024).

2.8 Research Framework

Based on the existing UTAUT2 model and the relevant literature, a customized analytical framework has been developed to guide the empirical phase of this research. Figure 1Research Framework illustrates this tailored research framework.

Figure 1 Research Framework



3 Methodology

This study employed a quantitative methodology to systematically examine the influence of technology adoption factors on Saudi government employees' willingness to embrace AI technologies. This approach was chosen for its effectiveness in testing hypotheses and exploring relationships among various research variables (Creswell, 2014). Questionnaires were utilized as the primary data collection tool, aligning with the study's goals to gather quantitative data (Saunders et al., 2019).

3.1 Questionnaire Development

The questionnaire development process involved document analysis, a systematic method for examining existing literature (Bowen, 2009). Initially, 75 items were identified, then refined to 20 questions (Appendix 1) to focus on the most relevant areas. A Likert scale was employed in the questionnaire, where "1" corresponds to strongly disagree and "5" corresponds to strongly agree, to measure respondents' attitudes and perceptions towards AI technologies, providing a detailed view of their readiness and acceptance levels.

To ensure the validity and reliability of the data collected, the questionnaire was translated from English to Arabic, considering the primary language of the respondents (Saunders et al., 2019). The questionnaire was translated using a systematic approach to maintain the integrity and accuracy of the instrument. It was initially translated from English to Arabic by a professional translator fluent in both languages, with a background in research methodology. To ensure accuracy, another independent translator conducted a back-translation process with no involvement in the initial translation. The original English version, the translated Arabic version, and the back-translated English version were then compared. Any discrepancies were discussed and resolved by the researcher and translators.

3.2 Sampling and Population

The study's population consisted of Saudi government employees, estimated to be approximately 1.2 million individuals (General Authority for Statistics, 2024). Given this population's large and dispersed nature, a representative sample of 103 participants was selected for the research. This appropriate sample size was determined using G*Power software, with the configuration details provided in Appendix 2. This calculation ensured sufficient power to detect the effects under investigation, maintaining the study's validity and reliability.

3.3 Data Analysis

Descriptive analysis was conducted on demographic variables such as age and gender to understand the characteristics of the sample population. Out of 117 total responses, 94 were male (80.3%) and 23 were female (19.7%). The age distribution of respondents was as follows: 57.3% were aged 35-44, 31.6% were aged 25-34, 6.8% were aged 45-54, 2.6% were aged 16-24, and 6.8% were aged 55-64. This demographic profile provided insights into the respondent characteristics and helped in data segmentation for further analysis.

partial least square structural equation modelling PLS-SEM was employed to test the theoretical model and the relationships between observed and latent variables. SEM is a comprehensive statistical technique that allows for assessing complex relationships among multiple variables, making it particularly suitable for this research (Kline, 2011). PLS-SEM is well-suited for theory development and exploratory research, particularly when the proposed model is innovative or lacks extensive prior testing (Joe et al., 2017). SmartPLS statistical software was utilized for data preparation and analysis. It facilitated the detection of outliers, helped determine the validity and reliability of the study, and ensured that the research was conducted with minimal errors and consistent findings.

3.4 Measurement Model Assessment

Having established the theoretical framework and methodologies for exploring the adoption of AI technologies among Saudi government employees, we now assess the measurement model utilized in this study. The following sub-section examines the reliability and validity of the constructs derived from the UTAUT2 model, ensuring that they accurately capture the various factors influencing AI adoption.

3.4.1 Reliability and Validity

Since the measurements in this study were extended and adapted from previous research, both validity and reliability were thoroughly tested.

3.4.1.1 Reliability

The reliability of the constructs was evaluated using Cronbach's Alpha and Composite Reliability (CR). Table 1 shows that most constructs demonstrated acceptable reliability, with CR values exceeding the recommended threshold of 0.7 (Heinzl et al., 2011). While Facilitating Conditions (FC) and Price Value (PV) had Cronbach's Alpha values slightly below 0.7, their CR values were above 0.7, indicating sufficient reliability. Furthermore, the standardized factor loadings for the items ranged from 0.560 to 0.925, which is above the required value of 0.50 (Gefen et al., 2000), further supporting the reliability of the constructs. Following Chin's (1998) guideline of removing items with loadings below 0.5 to ensure model reliability, BI4 was dropped due to its factor loading of 0.478.

Table 1 Items Loading, Reliability, and Convergent Validity

	Factor Loading	Cronbach's alpha	Composite reliability (rho_c)	Average variance extracted (AVE)
PE		0.869	0.92	0.792
PE1	0.883			
PE2	0.899			
PE3	0.881			
EE		0.749	0.856	0.665
EE1	0.771			
EE2	0.814			
EE3	0.859			
FC		0.585	0.746	0.505
FC1	0.886			
FC2	0.56			
FC3	0.645			
SI		0.874	0.922	0.798
SI1	0.88			

SI2	0.89			
SI3	0.91			
PV		0.591	0.827	0.706
PV1	0.789			
PV2	0.889			
PI		0.843	0.906	0.763
PI1	0.906			
PI2	0.891			
PI3	0.82			
BI		0.906	0.941	0.841
BI1	0.914			
BI2	0.913			
BI3	0.925			

3.4.1.2 Validity

Convergent validity was assessed using the Average Variance Extracted (AVE), with acceptable values exceeding 0.5 as shown in Table 1 indicating that all constructs explained a substantial portion of the variance in their indicators (Fornell & Larcker, 1981). This assures that all the items within each construct measure the same underlying latent variable .

Discriminant validity was confirmed using the Fornell-Larcker criterion and cross-loadings. **Table *2*** demonstrates that each construct's square root of AVE is higher than its correlations with other constructs, while Table 0 2 displays the Fornell-Larcker criterion affirming adequate discriminant validity (Fornell & Larcker, 1981). Furthermore, the cross loading illustrates that all indicators load more highly on their corresponding constructs than on others, reinforcing the validity of the constructs used in this study (**Table *3***) (Hair et al., 2011). Additionally, the Heterotrait-Monotrait ratio (HTMT), as shown in **Table *4*Table *2***, confirms the discriminant validity with all values below the critical threshold of 0.90, ensuring that the constructs are distinctly measured (Henseler et al., 2015), separate from each other, and suitable for examining AI technology adoption among Saudi government employees.

Table 2 Discriminate Validity – Fornell Larcker

	BI	**EE**	**FC**	**PE**	**PI**	**PV**	**SI**
BI	0.917						
EE	0.432	0.815					
FC	0.599	0.581	0.710				
PE	0.600	0.358	0.505	0.890			
PI	0.812	0.487	0.567	0.673	0.873		
PV	0.420	0.198	0.527	0.276	0.382	0.840	
SI	0.490	0.327	0.421	0.531	0.528	0.286	0.893

Table 3 Discriminate Validity – cross loading

	BI	EE	FC	PE	PI	PV	SI
PE							
PE1	0.562	0.326	0.442	0.888	0.645	0.264	0.548
PE2	0.516	0.311	0.465	0.899	0.562	0.257	0.365
PE3	0.522	0.318	0.442	0.883	0.585	0.216	0.495
EE							
EE1	0.307	0.771	0.332	0.196	0.373	0.07	0.202
EE2	0.334	0.814	0.445	0.264	0.355	0.136	0.209
EE3	0.406	0.859	0.61	0.391	0.453	0.254	0.367
FC							
FC1	0.623	0.623	0.886	0.549	0.61	0.351	0.408
FC2	0.212	0.235	0.56	0.101	0.155	0.557	0.127
FC3	0.271	0.196	0.645	0.235	0.246	0.399	0.276
SI							
SI1	0.376	0.245	0.354	0.462	0.412	0.27	0.88
SI2	0.444	0.341	0.348	0.453	0.491	0.298	0.89
SI3	0.481	0.286	0.421	0.505	0.501	0.206	0.91
PV							
PV1	0.297	0.043	0.386	0.133	0.262	0.789	0.22
PV2	0.399	0.26	0.49	0.308	0.37	0.889	0.259
PI							
PI1	0.733	0.402	0.538	0.6	0.906	0.365	0.469
PI2	0.695	0.436	0.443	0.601	0.891	0.357	0.422
PI3	0.697	0.438	0.501	0.561	0.821	0.278	0.491
BI							
BI1	0.915	0.4	0.576	0.603	0.742	0.369	0.51
BI2	0.912	0.391	0.55	0.536	0.725	0.431	0.414
BI3	0.925	0.398	0.521	0.508	0.767	0.356	0.421

Table 4 Discriminate Validity- Heterotrait-monotrait ration (HTMT)

	BI	EE	FC	PE	PI	PV	SI
BI							
EE	0.519						
FC	0.685	0.696					
PE	0.674	0.430	0.560				

PI	0.929	0.608	0.647	0.784		
PV	0.564	0.309	0.994	0.365	0.530	
SI	0.544	0.390	0.511	0.604	0.610	0.398

3.5 Structural Model Evaluation (Hypothesis Testing)

The structural model was evaluated to determine the significance of the hypothesized relationships between the constructs and their effect on Behavioural Intention (BI). The bootstrapping procedure was used with 5,000 subsamples to estimate the path coefficients, t-values, and p-values, ensuring robust and reliable statistical inference. The results are summarized in Table 5, providing a detailed overview of the direct effects within the model.

Table 5 Path Coefficients Significance of UTAUT2 Constructs

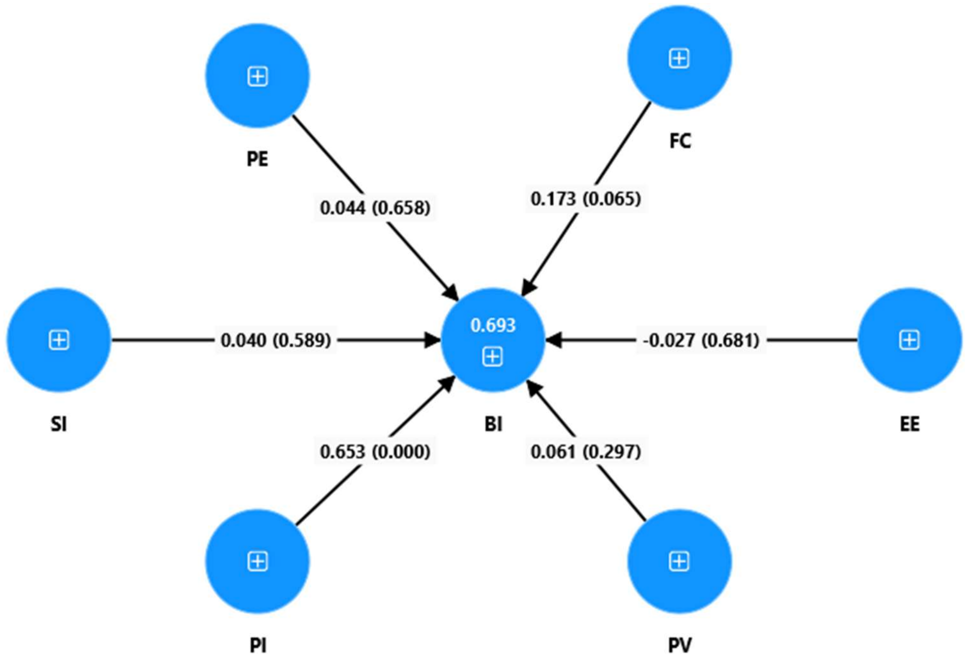
Hypothesis	Beta Coefficient	Standard deviation	T statistics	P values	Significance
PE -> BI	0.044	0.099	0.442	0.658	Not Significant
EE -> BI	-0.027	0.065	0.411	0.681	Not Significant
SI -> BI	0.04	0.073	0.54	0.589	Not Significant
FC -> BI	0.173	0.094	1.848	0.065	Not Significant
PV -> BI	0.061	0.058	1.043	0.297	Not Significant
PI -> BI	0.653	0.081	8.033	0	Significant

3.5.1 Path Coefficients and Hypothesis Testing

The structural model evaluation revealed that the model explains 69.3% of the variance in Behavioural Intention (BI) ($R^2 = 0.693$). This suggests that the independent variables included in the model (PE, EE, SI, FC, PV, and PI) collectively provide substantial explanatory power for predicting Behavioural Intention according to Chin W.W. (1998), which indicates that the model effectively captures the key factors influencing Saudi government employees' behavioural intention to embrace AI technologies.

Among the six hypothesized relationships with BI, only the path from Personal Innovativeness to BI was statistically significant ($\beta = 0.653$, $t = 8.033$, $p < 0.001$), demonstrating a significant positive influence and identifying it as a key determinant in this context. In contrast, the paths from Effort Expectancy ($\beta = -0.027$, $t = 0.411$, $p = 0.681$), Performance Expectancy ($\beta = 0.044$, $t = 0.442$, $p = 0.658$), Perceived Value ($\beta = 0.061$, $t = 1.043$, $p = 0.297$), and Social Influence ($\beta = 0.040$, $t = 0.540$, $p = 0.589$) were not significant at the 0.05 level, suggesting that these factors do not significantly impact Behavioural Intention in this context. However, the relationship between Facilitating Conditions and BI ($\beta = 0.173$, $t = 1.848$, $p = 0.065$) was marginally above the significance threshold, indicating it may be considered partially significant, suggesting a potential, though weak, influence on Behavioural Intention that warrants further investigation.   displays the structural model. Figure 2 displays the research structural model.

Figure 2 Structural Model



The F-square values further assess the impact of each predictor on Behavioural Intention. Effect size, as measured by the f-square value, is interpreted based on the following thresholds: values of 0.02 or higher indicate a small effect, 0.15 or higher represent a medium effect, and 0.35 or higher signify a large effect (Cohen, 1988). Personal Innovativeness shows a large effect size (f^2 = 0.591), confirming its role as a key determinant of Behavioural Intention. In contrast, Facilitating Conditions has a small effect size (f^2 = 0.042), suggesting a minimal influence on BI. All other predictors, including Effort Expectancy (f^2 = 0.001), Performance Expectancy (f^2 = 0.003), Perceived Value (f^2 = 0.008), and Social Influence (f^2 = 0.003), show negligible effect sizes, indicating that they do not significantly contribute to the variance in Behavioural Intention in this context.

4 Results and Discussion

This study investigated the factors influencing Saudi government employees' willingness to adopt AI technologies using an extended Unified Theory of Acceptance and Use of Technology (UTAUT2) framework. The model incorporated six key variables: performance expectancy, effort expectancy, social influence, facilitating conditions, price value, and a newly introduced variable, personal innovativeness. Data from 117 respondents were analyzed using Structural Equation Modelling (SEM) with SmartPLS 4.0. Contrary to the assumptions of the original UTAUT model (Venkatesh et al., 2012, 2016), most determinants did not significantly influence AI adoption among Saudi government employees, with only one showing a meaningful impact.

Performance Expectancy (H1): The analysis showed that PE does not significantly impact the intention of Saudi government employees to adopt AI technologies. This result diverges from studies emphasizing PE as a critical determinant of behavioural intention in technology adoption (Almahri et al., 2020; Chu et al., 2022; Jain et al., 2022; Tanantong &

Wongras, 2024). However, the findings align with García de Blanes Sebastián et al. (2022), who found no significant impact of PE on users' intention to adopt AI virtual assistants. Similarly, Basaran and Mohamed (2020) reported a weak relationship between PE and technology use intention, suggesting that other factors may take precedence over performance expectations for users already familiar with the technology. This supports the notion that as users gain more experience, the influence of PE on behavioural intentions diminishes, shifting the focus to other determinants.

Effort Expectancy (H2): The results indicate that EE does not significantly influence Saudi government employees' intention to adopt AI technologies. This is consistent with studies by Balakrishnan and Dwivedi (2024) and Aw et al. (2022), who found that perceived ease of use did not significantly affect the use of AI-powered digital assistants or AI digital voice assistants, respectively. Similarly, Korkmaz et al. (2021) noted no impact of EE on the intention to use AI-Autonomous Public Transport systems, suggesting that perceived ease of use may be less critical when dealing with more advanced or less familiar technologies. These findings collectively highlight that, contrary to traditional beliefs, perceived ease of use is not always a decisive factor in the adoption of new technologies, particularly in contexts involving more advanced technologies.

Social Influence (H3): The analysis revealed that SI did not significantly affect the behavioural intention of Saudi government employees to adopt AI technologies. While some studies highlight the importance of social influence in technology adoption (Muhardi Saputra et al., 2021; Zefreh et al., 2023), other research supports the present findings, showing minimal or no effect of SI in contexts such as AI decision-making (Cao et al., 2021), customer relationship management acceptance (Chatterjee et al., 2023), and AI acceptance in higher education (Chatterjee & Bhattacharjee, 2020). Additionally, no significant influence was found in adopting AI virtual assistants (García de Blanes Sebastián et al., 2022) or AI in human resource recruitment (Tanantong & Wongras, 2024). This suggests that employees in the Saudi public sector may prioritize personal judgment or other factors over social cues when considering AI adoption.

Facilitating Conditions (H4): The analysis indicated that FC has a partially significant impact on the behavioural intention of Saudi government employees to adopt AI technologies. While the availability of resources, support, and infrastructure may play a role, they are not the dominant factors driving AI adoption within this research context. This observation aligns with previous studies by Almahri et al. (2020), Chu et al. (2022), and García de Blanes Sebastián et al. (2022), which also found limited influence of FC on technology adoption intentions. The partial significance observed in this study suggests that while employees may recognise the importance of resources, support, or infrastructure, these factors alone are insufficient to compel adoption unless other motivational factors are also strong.

Price Value (H5): The analysis found that PV is not a significant factor influencing the behavioural intention of Saudi government employees to adopt AI technologies. This finding can be attributed to the substantial financial resources allocated by the Saudi government to invest in emerging technologies, including AI (Alghamdi et al., 2023; Cabral, 2023; Solaiman et al., 2024). Consequently, employees may not view cost as a major concern, either because they are not directly responsible for the financial aspects of AI implementation or because they perceive the benefits of AI to outweigh its costs. This is consistent with other studies where PV did not significantly impact the adoption of AI virtual assistants (García de Blanes Sebastián et al., 2022) or autonomous public transport systems (Korkmaz et al., 2021).

Personal Innovativeness (H6): In contrast, the study's findings demonstrate a significant positive relationship between PI and behavioural intention (BI), indicating that employees who are more open to experimenting with new technologies are more likely to adopt AI. This finding supports earlier studies by Baabdullah et al. (2016) and Badwelan et al. (2016), reinforcing the idea that innovative individuals tend to be more optimistic and proactive when faced with new technologies (Dabholkar & Bagozzi, 2002; Kalinić et al., 2019). Given AI's novel and transformative potential, fostering a culture of innovation and curiosity among employees could be crucial for enhancing AI adoption in the Saudi public sector.

5 Conclusion and Implications

This study explored the factors influencing Saudi government employees' willingness to adopt AI technologies using an extended Unified Theory of Acceptance and Use of Technology (UTAUT2) model. The findings indicate that traditional factors such as performance expectancy, effort expectancy, social influence, facilitating conditions, and price value did not significantly affect AI adoption in this context. Instead, personal innovativeness emerged as a critical determinant, highlighting the importance of individual traits in shaping technology adoption behaviours among public sector employees. These results suggest that adopting AI technologies in government settings may be driven by factors beyond those identified in the original UTAUT2 model.

5.1 Theoretical Contributions

This study enhances the understanding of technology adoption by extending the UTAUT2 model to include the construct of personal innovativeness. The findings reveal that personal innovativeness is a significant predictor of AI adoption among Saudi government employees, underscoring the importance of individual traits such as openness to new experiences and willingness to experiment with new technologies. By adding this construct, the study offers valuable insights into how personal characteristics can influence technology acceptance, providing a fresh perspective on factors that drive adoption in the public sector.

In addition to incorporating this new variable, the study refined the UTAUT2 model by eliminating constructs deemed irrelevant to the research context, such as habit, hedonic motivation, and use behaviour. These constructs, while meaningful in other settings, were not applicable in this study of AI adoption among public sector employees. This selective approach ensures that the model better reflects the unique characteristics of the public sector environment, allowing for more accurate and context-specific insights..

5.2 Practical Contributions

From a practical perspective, the study offers valuable guidance for policymakers, government agencies, and technology developers seeking to enhance AI adoption in the public sector. The identification of personal innovativeness as a significant factor suggests that efforts should focus on fostering a culture of innovation and curiosity among employees. This could be achieved through targeted initiatives such as training programs, workshops, and opportunities for hands-on experimentation with new technologies.

Moreover, the findings indicate that traditional factors like perceived ease of use and social influence may not be as influential in this context. Therefore, strategies should focus on building trust in AI systems, ensuring robust organizational support, and effectively communicating the benefits and practical applications of AI technologies. By understanding and addressing these nuanced drivers of adoption, organizations can create more tailored and effective approaches to promoting AI technologies among their employees.

6. Limitations and future research

While this study offers valuable insights into the factors influencing Saudi government employees' willingness to adopt AI technologies, it also highlights several areas for further research to build on these findings. First, the study was limited to non-military and non-national security government entities due to the sensitivity of their operations.

Additionally, the study focused on a specific sample of Saudi government employees using a non-random sampling method. Future research could enhance the generalisability of the results by employing a more systematic sampling approach and extending the investigation to include a wider range of employees from various regions and governmental and private sector organisations. Such efforts would broaden the applicability and robustness of the findings across different contexts.

Moreover, the cross-sectional design of this study provided a snapshot of employee attitudes and intentions at a single point in time. However, given the rapid evolution of AI technologies, there is potential for future research to adopt longitudinal or experimental designs to explore how employee attitudes and willingness to adopt AI change over time or in response to specific interventions. These approaches could yield richer insights into the dynamic nature of behavioural intentions and the factors that promote sustained interest in adopting new technologies as they evolve.

Finally, while this research effectively utilised the extended UTAUT2 framework to examine variables such as performance expectancy, effort expectancy, social influence, facilitating conditions, price value, and personal innovativeness, there remains room to expand the scope. Future studies could enrich this framework by considering additional factors like organisational culture, leadership support, or trust, providing a more comprehensive view of the diverse influences on employee behaviour regarding AI adoption.

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Appendix

APPENDIX 1 Compilation of items from past studies

Construct	Code	Sources
Performance Expectancy	PE1	1. The usage of m-commerce increases the chances to achieve things which are
		2. Using smart meter system would make me work more efficiently (Alkawsi et
		3. Using autonomous shuttles will help me reach my destination in a more comf
	PE2	4. The APTS would be an important part of the existing public transport system
		5. Using an IoT system will assist in weather forecasting in crop production (Sh
	PE3	6. SIMPATIK is very useful for my daily work activity (Muhardi Saputra et al.,
		7. I find smart meter system useful for me (Alkawsi et al., 2021)
		8. I find IoT systems useful in crop yield rate analysis (Shi et al., 2022)
Effort Expectancy	EE1	9. It would not take a long time to learn how to use the APTS (Korkmaz et al., 2
		10. Learning how use smart meter system is easy for me (Alkawsi et al., 2021)
		11. The IoT is easy to learn for me (Shi et al., 2022)
		12. Learning to operate the system is easy for me (Adell & Lund, 2010)
		13. Learning to operate autonomous vehicle would be easy for me (Choi & Ji, 201
	EE2	14. SIMPATIK is easy to use
		15. I would find the system easy to use (Muhardi Saputra et al., 2021)
		16. I find autonomous shuttles easy to use (Rombaut et al., 2020)
		17. It would be easy to understand how to use the APTS (Korkmaz et al., 2021)
		18. I would find the system easy to use (Adell & Lund, 2010; Venkatesh et al., 20
		19. I find smart meter system easy to use (Alkawsi et al., 2021)

		20. I find the IoT simple to use (Shi et al., 2022)
		21. I find the ARTS easy to use (Madigan et al., 2017)
		22. I would find it easy to get autonomous vehicle to do what I want to do. (Choi
	EE3	23. My interaction with the system would be clear and understandable (Adell & L
		24. My interaction with smart meter system is clear and understandable (Alkawsi
		25. My interaction with the ARTS is clear and understandable (Madigan et al., 20
Social Influence	SI1	26. People who important to me is suggest me of using SIMPATIK (Muhardi Sap
		27. People who are important to me would think that I should use the APTS (Kor
		28. People who are important to me think that I should use the smart meter system
		29. People who are important to me think that I should use the system (Venkatesh
		30. People who are important to me think that I should use ARTS (Madigan et al.,
		31. People who matter to me suggest I should utilize the IoT in agriculture.(Shi et
	SI2	32. People who can influence me think that I should use SIMPATIK (Muhardi Sa
		33. People who influence my behaviour think that I should use the smart meter sy
		34. People who influence my behavior think that I should use ARTS (Madigan et
		35. I would probably use the APTS if people who influence my behavior think th
		36. People who shape my behavior suggest I should utilize the IoT in agriculture (
	SI3	37. People whose opinions I value would like me to use the APTS (Korkmaz et al
		38. People whose opinions that I value prefer that I use smart meter system (Alka
		39. People whose opinions I value would like me to use ARTS (Madigan et al., 2
		40. People I respect desire that I employ the IoT in agriculture production.(Shi et
Facilitating Conditions	FC1	41. I have the knowledge necessary to use smart meter system (Alkawsi et al., 20
		42. I have the knowledge necessary to use the APTS (Korkmaz et al., 2021)
		43. I know how to apply the IoT in agriculture (Shi et al., 2022)
		44. I have the knowledge necessary to use the system (Venkatesh et al., 2003)
	FC2	45. I have an enough resource to access SIMPATIK like smartphone (Muhardi Sa
		46. I have the resources necessary to use smart meter system (Alkawsi et al., 2021
		47. I have the resources necessary to use the APTS (Korkmaz et al., 2021)(
		48. I am well equipped to put the IoT to work in agricultural productivity.(Shi et
		49. I have the resources necessary to use the system (Venkatesh et al., 2003)
		50. I have the resources necessary to use ARTS (Madigan et al., 2017)
	FC3	51. When I encounter challenges in implementing the IoT in agriculture productio
		52. I can get help from others when I have difficulties using smart meter system (
		53. I can get help from others when I have difficulties using the ARTS (Madigan
		54. I can ask a question to other people if I have a problem of using SIMPATIK (
Price Value	PV1	55. The APTS usage would be reasonably priced (Korkmaz et al., 2021)
		56. The APTS would be a good value for the money (Korkmaz et al., 2021)
	PV2	57. In general, the organization has supported the use of the system (Venkatesh et
		58. In general, the organization has supported the use of the system (Madigan et a
Personal Innovativeness	PI1	59. I like to try new things (Shi et al., 2022)
		60. I like to try new things (Alkawsi et al., 2021)
	PI2	61. I would not hesitate to use new agricultural technology (Shi et al., 2022)

		62. I would not hesitate to try out new information technology (Alkawsi et al., 202
	PI3	63. Among other entrepreneurs, I am usually the first to try out new agricultural te
		64. Among my fellows, I am usually the first to try out new information technolog
Behavioral Intention	BI1	65. I intend to use the system in the next <n >months (Venkatesh et al., 2003)
		66. I intend to continue using mobile Internet in the future. (Venkatesh et al., 2012
		67. I intend to continue using smart meter system in the future (Alkawsi et al., 202
		68. I intend to use ARTS again during the demonstration period (Madigan et al., 2
		69. I intend to use autonomous vehicle in the future (Choi & Ji, 2015)
		70. mobile Internet in my daily life. (Venkatesh et al., 2012)
		71. I plan to use IoT systems in agricultural production in the future. (Shi et al., 20
		72. I intend to use autonomous shuttles in the future (Rombaut et al., 2020)
		73. I have positive experience when it co(San-Martin & López-Catalán, 2013)an-l
	BI2	74. I plan to continue to use the smart meter system frequently (Alkawsi et al., 202
		75. I predict I would use the system in the next <n >months (Venkatesh et al., 200
	BI3	76. I am satisfied with the product range offered by online retailers (Gupta et al., 2

Construct	Code	Sources	Modified Item
Performance Expectancy	PE1	1. The usage of m-commerce increases the chances to achieve things which are very important to me (Venkatesh et al., 2003) 2. Using smart meter system would make me work more efficiently (Alkawsi et al., 2021) Using autonomous shuttles will help me reach my destination in a more comfortable way (Rombaut et al., 2020)	1. I believe that using AI technologies will make me work more efficiently
	PE2	3. The APTS would be an important part of the existing public transport systems (Korkmaz et al., 2021) Using an IoT system will assist in weather forecasting in crop production (Shi et al., 2022)	2. I expect AI technologies to enhance the quality of services provided to our clients/citizens.

	PE3	4. SIMPATIK is very useful for my daily work activity (Muhardi Saputra et al., 2021) . I find smart meter system useful for me (Alkawsi et al., 2021) I find IoT systems useful in crop yield rate analysis (Shi et al., 2022)	3. I believe that AI technologies will help me in my daily tasks such as make better decisions and solve problems more effectively.
Effort Expectancy	EE1	6. It would not take a long time to learn how to use the APTS (Korkmaz et al., 2021) 7. Learning how use smart meter system is easy for me (Alkawsi et al., 2021) 8. The IoT is easy to learn for me (Shi et al., 2022) 9. Learning to operate the system is easy for me (Adell & Lund, 2010) Learning to operate autonomous vehicle would be easy for me (Choi & Ji, 2015)	4. Learning to use AI tools and systems will require minimal effort on my part.
	EE2	10. SIMPATIK is easy to use 11. I would find the system easy to use (Muhardi Saputra et al., 2021) 12. I find autonomous shuttles easy to use (Rombaut et al., 2020) 13. It would be easy to understand how to use the APTS (Korkmaz et al., 2021)	I believe it will be easy to understand how to use AI technologies

		4. I would find the system easy to use (Adell & Lund, 2010; Venkatesh et al., 2003) 15. I find smart meter system easy to use (Alkawsi et al., 2021) 6. I find the IoT simple to use (Shi et al., 2022) 17. I find the ARTS easy to use (Madigan et al., 2017) I would find it easy to get autonomous vehicle to do what I want to do. (Choi & Ji, 2015)	
	EE3	8. My interaction with the system would be clear and understandable (Adell & Lund, 2010) 9. My interaction with smart meter system is clear and understandable (Alkawsi et al., 2021) My interaction with the ARTS is clear and understandable (Madigan et al., 2017)	My interactions with AI technologies at work are clear and understandable
Social Influence	SI1	20. People who important to me is suggest me of using SIMPATIK (Muhardi Saputra et al., 2021) 1. People who are important to me would think that I should use the APTS (Korkmaz et al., 2021) 2. People who are important to me think that I should use the smart	People who are important to me believe that I should use AI technologies in my work.

		meter system (Alkawsi et al., 2021) 3. People who are important to me think that I should use the system (Venkatesh et al., 2003) 4. People who are important to me think that I should use ARTS (Madigan et al., 2017) . People who matter to me suggest I should utilize the IoT in agriculture.(Shi et al., 2022)	
	SI2	25. People who can influence me think that I should use SIMPATIK (Muhardi Saputra et al., 2021) 26. People who influence my behaviour think that I should use the smart meter system (Alkawsi et al., 2021) 27. People who influence my behavior think that I should use ARTS (Madigan et al., 2017) 8. I would probably use the APTS if people who influence my behavior think that I should use the APTS (Korkmaz et al., 2021) People who shape my behavior suggest I should utilize the IoT in agriculture (Shi et al., 2022)	Influential people in my life think that I should adopt AI technologies in my work.

	SI3	29. People whose opinions I value would like me to use the APTS (Korkmaz et al., 2021) 30. People whose opinions that I value prefer that I use smart meter system (Alkawsi et al., 2021) 31. People whose opinions I value would like me to use ARTS (Madigan et al., 2017) People I respect desire that I employ the IoT in agriculture production.(Shi et al., 2022)	Colleagues whose opinions I value prefer that I use AI technologies in my daily tasks.
Facilitating Conditions	FC1	2. I have the knowledge necessary to use smart meter system (Alkawsi et al., 2021) 3. I have the knowledge necessary to use the APTS (Korkmaz et al., 2021) 34. I know how to apply the IoT in agriculture (Shi et al., 2022) I have the knowledge necessary to use the system (Venkatesh et al., 2003)	1. I have the necessary knowledge to use AI technologies in my job.
	FC2	35. I have an enough resource to access SIMPATIK like smartphone (Muhardi Saputra et al., 2021) 5. I have the resources necessary to use smart meter system (Alkawsi et al., 2021)	My organization provides the resources (e.g., internet access, devices) necessary to use artificial intelligence tools

		7. I have the resources necessary to use the APTS (Korkmaz et al., 2021)(38. I am well equipped to put the IoT to work in agricultural productivity.(Shi et al., 2022) 9. I have the resources necessary to use the system (Venkatesh et al., 2003) I have the resources necessary to use ARTS (Madigan et al., 2017)	
	FC3	0. When I encounter challenges in implementing the IoT in agriculture production, I can ask for assistance from others (Shi et al., 2022) 1. I can get help from others when I have difficulties using smart meter system (Alkawsi et al., 2021) 2. I can get help from others when I have difficulties using the ARTS (Madigan et al., 2017) I can ask a question to other people if I have a problem of using SIMPATIK (Muhardi Saputra et al., 2021)	. I can get help from my colleagues when I have difficulties using AI tools
Price Value	PV1	43. The APTS usage would be reasonably priced (Korkmaz et al., 2021)	The cost of adopting AI technologies within my organization is reasonable and affordable.

		44. The APTS would be a good value for the money (Korkmaz et al., 2021) 16.	
	PV2	45. In general, the organization has supported the use of the system (Venkatesh et al., 2003) In general, the organization has supported the use of the system (Madigan et al., 2017)	In general, the organization I work for provides strong financial support for the adoption of AI technologies.
Personal Innovativeness	PI1	46. I like to try new things (Shi et al., 2022) I like to try new things (Alkawsi et al., 2021)	I am eager to explore and adopt new AI technologies in my work. 21.
	PI2	47. I would not hesitate to use new agricultural technology (Shi et al., 2022) I would not hesitate to try out new information technology (Alkawsi et al., 2021)	I would not hesitate to try out new AI tools at work.
	PI3	48. Among other entrepreneurs, I am usually the first to try out new agricultural technology (Shi et al., 2022) 4. Among my fellows, I am usually the first to try out new information technology (Alkawsi et al., 2021)	Among my Colleagues, I am usually one of the first to adopt new AI technologies in my professional field.
Behavioral Intention	BI1	49. I intend to use the system in the next <n >months (Venkatesh et al., 2003) 50. I intend to continue using mobile Internet in the future. (Venkatesh et al., 2012)	6. I intend to use AI technologies in my job currently. . I plan to use AI in my job in the future 27.

		1. I intend to continue using smart meter system in the future (Alkawsi et al., 2021) 52. I intend to use ARTS again during the demonstration period (Madigan et al., 2017) 53. I intend to use autonomous vehicle in the future (Choi & Ji, 2015) 4. mobile Internet in my daily life. (Venkatesh et al., 2012) 55. I plan to use IoT systems in agricultural production in the future. (Shi et al., 2022) 56. I intend to use autonomous shuttles in the future (Rombaut et al., 2020) I have positive experience when it co(San-Martin & López-Catalán, 2013)an-Martin & López-Catalán, 2013)	
	BI2	57. I plan to continue to use the smart meter system frequently (Alkawsi et al., 2021) I predict I would use the system in the next <n >months (Venkatesh et al., 2003)	I plan to continue exploring new AI tools and systems in my field.
	BI3	I am satisfied with the product range offered by online retailers (Gupta et al., 2023)	I am satisfied with the AI tools offered at my work place

Appendix 2 G*Power configuration details used to determine the sample size

Parameter	Value
Test family	F
Statistical test	Linear multiple regression: Fixed model, R^2 deviation from zero
Type of power analysis	A priori: Compute required sample size
Effect size f^2	0.15
Alpha error probability	0.05
Power (1-β error probability)	0.80
Number of predictors	7
Total Sample Size	103