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# The effects of the internal and the external factors affecting artificial intelligence (AI) adoption in e-innovation technology projects in the UAE? Applying both innovation and technology acceptance theories

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A B S T R A C T

This study has examined factors, such as technology and employee influence on artificial intelligence (AI) adoption of e-innovative projects in the United Arab Emirates. The present study revealed the success or failure of e-innovation adoption in the public sector of the UAE and hinted at potential e-innovative projects to consider essential factors before adopting it. The study's sample covered the government sector, and the data collection method was a survey questionnaire with a sample size of 1037 responses made up of government employees. This paper was mainly built upon the diffusion of innovation and technology acceptance theories. The analysis findings showed that technology (an external factor) significantly and positively contributed to adopting AI e-innovation technology. Further analysis revealed that employee (internal factor) proxies directly influenced the adoption of AI e-innovation technology. Overall, internal and external factors contributed to adopting e-innovation technology in the United Arab Emirates. For future directions, additional factors related to the market should be considered to explore their contribution.



## 1. Introduction

Innovation is a source of growth (Romer, 1987). Innovation is a continuous process of creating new ideas in products and services, which relies heavily on platforms and the environment (Hasan *et al.*, 2017). The high-speed growth of information technology has forced organizations to rapidly and quickly change innovation in the digital business area or environment (Hasan *et al.*, 2017). The link between innovation and digital technology has borne the term "e-innovation", which has been used for the last three decades (Lan & Du, 2002). e-innovation is associated with; planning, scenario building, technological forecasting, market intelligence, new product and business developments and forming new ideas as a proactive response to change.

In light of the COVID-19 epidemic, public sector organizations faced a strategic challenge that prompted them to reevaluate their business practices and introduce more uncertainty and volatility into their budgeting (Mora Cortez & Johnston, 2020). Government institutions in the United Arab Emirates (UAE) saw similar effects from the global financial crisis of 2008to those in other countries. However, the crisis also prompted new approaches to providing public services (Alosani & Al-Dhaafri, 2023). Despite the importance of innovation in the United Arab Emirates government sector, few studies have been conducted on the topic, especially regarding the variables stimulating innovation in the service sector (Alosani & Al-Dhaafri, 2023).

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Why choose to examine the United Arab Emirates? The UAE is the regional leader in innovation practices, such as; smart economy, artificial intelligence (AI) and human capital (Khan, 2019). Since countries are fragmented and controlled into various state and non-state entities, innovation is a possible survival strategy. The UAE has implemented various innovative strategies and provided innovation platforms for local and foreign investors in different business sectors. Also, the UAE initiated an innovation program to become a knowledge-based economy. This process was further fueled after the "2015 Year of Innovation" implemented by the UAE government. The government's vision was that the UAE would become ranked first in the world in innovation (Dulaimi, 2021). The United Arab Emirates (UAE) has decided in 2019 to help realize the ambitions of aspiring entrepreneurs all throughout the Gulf region by pooling resources to accelerate technology advancement and capitalizing on it (Khan, 2019). Innovations, such as; smartphones, Web 2.0, e-marketing, e-commerce, e-banking and e-health, have become essential in people's everyday lives (Zolait, 2020). Information Technology (IT) e-innovation is a platform adopted by the private and public sectors globally. Individuals also utilize e-innovation products to fulfil their daily needs (Zolait, 2020).

E-innovation projects fail when organizations abandon e-innovations before introducing them to the market (D'Attoma & Ieva, 2020; Tranekjer, 2017). Despite the rising adoption of e-innovation, up to 90% of such projects fail (Kuester *et al.*, 2018; Marmer *et al.*, 2011). This outcome is typically due to e-innovations applying high levels of uncertainty for potential users, especially startup e-innovations. Several important characteristics of e-innovations provided by startups cause this uncertainty. These characteristics include; their digital nature, intangibility, newness and impersonality, and unfamiliarity with the launching organization (Huang & Rust, 2013; Kuester *et al.*, 2018). Moreover, uncertainty grows with privacy concerns and the fear of data misuse (Kuester *et al.*, 2018).

The present paper's motivation came from the research of Badi *et al.* (2021), which examined: organization, market, and technological factors influencing smart e-innovation contract adoption in the United Kingdom's construction sector. However, they didn't undertake employee-related factors. As a result, the present research was motivated to test technology (external) and employees'(internal) factors and apply them to the UAE's public sector to understand the direction of the relationship. Thus, the present study focused on the successful adoption of e-innovation by considering two main factors: technology and employees. First, technology was represented by five different subfactors: perceived relative advantage, perceived compatibility, perceived complexity, perceived trialability and perceived observability (Carraher-Wolverton & Zhu, 2021; Rogers, 2010), perceived ease of use, and perceived usefulness (Davis, 1989; Lee *et al.*, 2011; S.H. Liu *et al.*, 2009; Park *et al.*, 2012; Salloum *et al.*, 2019). Second, employees had three dynamics: intrinsic motivation, extrinsic motivation (Siyal *et al.*, 2021) and perceived self-efficacy (Fuchs *et al.*, 2019). All these factors supported the adoption of e-innovation in the public sector.

The remainder of this paper is organized as follows. Section 2 reviews the existing literature regarding motivations and hypotheses creation. Section 3 details the methodology used in this study. In contrast, Section 4 discusses the empirical results. The discussion is considered in Section 5. The conclusion of the study is contained in Section 6. The final element of the paper contains the references.

## 2. Literature review and hypotheses

Institutionalizing e-innovation in the public sector can foster a "creative atmosphere," as defined by Zhu (2015), where the populace is open to new developments and improvements in the routine practices of the public sector, including; education and organizations. Technology-enabled innovation is sometimes called "e-innovation" (Martin, 2004). e-innovation refers to any innovative approach or paradigm for managing and advancing innovation in the digital realm (Lan, 2004). When applied to the current environment of rapid change, "e-innovation" may also refer to a novel concept or name for a set of activities aiming to develop methods for fostering; innovation, product creation, and corporate expansion (Hasan *et al.*, 2017). The internet has undoubtedly sparked the development of cutting-edge, commodities, services, and commercial practices. According to Carraher-Wolverton & Zhu (2021) and Rogers (2010), the adoption rate of e-innovation by society members has a relative speed that measures a new idea's adoption rate by the number of individuals or employees in a specified period.

Rogers Everett (1995) stated that the diffusion of innovation theory provided an insightful framework for understanding how a new idea spreads and will eventually be adopted. The theory is split into two phases: the first is the idea stage, and the second is the actualization stage. Once the novelty of a concept has been acknowledged, the next phase begins, in which individuals determine whether or not to adopt the idea (Ali *et al.*, 2019). Similarly, the diffusion of innovation theory describes how new ideas spread gradually throughout society through predetermined routes (Poong *et al.*, 2009; Rogers, 2003, 2010).

Another classic model is the "technology adoption model", developed by Davis (1989). It is a well-known model frequently used for research regarding technology acceptance. The TAM proposed that an individual's behavioral intention to embrace technology is jointly determined by the individual's perception of the technology's perceived usefulness and ease of use. Several research studies have applied the "technology adoption model" to determine the relationship between different factors influencing the adoption of e-innovation technology (Achjari & Quaddus, 2003; Chatterjee *et al.*, 2021; Hoang & Nguyen, 2022; Mondego & Gide, 2022; Pillai *et al.*, 2021; Poong *et al.*, 2009).

### 2.1 Technology and e-innovation adoption

Concepts evaluating e-innovation technology adoption include; the diffusion of innovation theory (Ali *et al.*, 2019; Rogers, 2003; Rogers, 1995) and the technology acceptance model (Alshurideh *et al.*, 2019; Chatterjee *et al.*, 2021; Davis, 1993). Besides, the adoption rate has been strongly related to several characteristics of e-innovation technology. These characteristics include; perceived relative advantage, compatibility, trialability, complexity, observability (Wolverton & Zhu, 2021; Rogers, 2010), ease of use and usefulness (Alshurideh *et al.*, 2019).

#### 2.1.1 Perceived relative advantage

Rogers (1995 & 2003, p.229) used the term "relative advantage" to describe the degree to which an invention is preferable. The idea of comparative advantage relies on certain features of innovation and the primary steps for embracing e-innovation (smart contracts) (Badi *et al.*, 2021). Likewise, the authors mentioned that the likelihood of widespread adoption of innovation increased dramatically if its perceived relative benefit was high. It has been determined that relative advantage is the degree to which a certain e-innovation is seen as superior to the use of earlier technologies to enhance work performance (Badi *et al.*, 2021; Y. Wang *et al.*, 2008). Many studies have found that perceived advantage had an insignificant influence on AI e-Innovation adoption. Examples include; 297 Chinese companies (Pan *et al.*, 2022), the banking sector of the US (Payne *et al.*, 2018), the banking sector of Indonesia (Yussaivi *et al.*, 2020), and the government sector of Jordan (Alomari *et al.*, 2012). Only a few studies have found a positive and significant relationship between perceived relative advantage and the intention to adopt e-innovation. Examples include; e-government services in Malaysia (Lean *et al.*, 2009) and social media marketing using firm-level data in 214 SMEs in Malaysia (Ali Abbasi *et al.*, 2022). Based on these considerations, the following hypothesis was proposed:

**$H_{1A}$:** *Perceived relative advantage positively influences artificial intelligence (AI) e-innovation adoption.*

#### 2.1.2 Perceived compatibility

Several studies have found that perceived compatibility had a statistically significant influence on e-Innovation adoption (Achjari & Quaddus, 2003; Chatterjee *et al.*, 2021; Hoang & Nguyen, 2022; Mondego & Gide, 2022; Pillai *et al.*, 2021; Poong *et al.*, 2009; Saffu *et al.*, 2008). When adopting new technologies, the degree to which they are compatible with potential adopters' existing values, experiences, and wants, is known as their "perceived compatibility" (Rogers, 2003, p.240). The ability to appreciate the benefits of innovation would be simpler for people with more experience (Kapoor *et al.*, 2014). Badi *et al.* (2021) highlighted that integrating e-innovation into an institution's preexisting technical framework was important. When a company's existing processes, attitudes, and beliefs are compatible with an e-innovative technology, that technology has a greater chance of being adopted (Badi *et al.*, 2021; Gutierrez *et al.*, 2015). Achjari & Quaddus, 2003) found that perceived compatibility had a significant role in Indonesian banks' diffusion of the World Wide Web (WWW). As per Chatterjee *et al.* (2021), perceived compatibility significantly influenced perceived utility since AI technology was compatible with the current format, technical architecture, and other structural data. Likewise, Pillai *et al.* (2021) studied 480 AI-empowered industrial robots in auto component manufacturing businesses in India and discovered that perceived compatibility was a good predictor of AI-empowered adoption in those manufacturing organizations. Therefore, the following hypothesis was proposed:

**$H_{1B}$:** *Perceived compatibility positively influences artificial intelligence (AI) e-innovation adoption.*

#### 2.1.3 Perceived complexity

Perceived complexity refers to the perception of innovation as challenging to comprehend and use (Joo *et al.*, 2014; Rogers, 2003, p.257). Similarly, Christiansen *et al.* (2022) stated that perceived complexity referred to the difficulty of learning, implementing and comprehending an e-innovation and that a complex e-innovation system had an inverse influence on the intention of adoption. Several studies have found that perceived complexity has a significant influence on AI e-Innovation adoption in both the government sector (Alomari *et al.*, 2012; Lean *et al.*, 2009; Liang & Lu, 2013) and the private sector (Chatterjee *et al.*, 2021; Pan *et al.*, 2022). It was found that perceived complexity had a negative and significant impact on AI e-innovation adoption in production and manufacturing in 340 companies in India (Chatterjee *et al.*, 2021), the government sector of Jordan (Alomari *et al.*, 2012), survey results from 297 firms of China (Pan *et al.*, 2022) and the government sector of Malaysia (Lean *et al.*, 2009). In contrast, Liang & Lu (2013) revealed that perceived complexity positively influenced AI e-innovation adoption in the financial sector of Taiwan. Consequently, the following hypothesis was proposed:

**$H_{1C}$:** *Perceived complexity negatively influences artificial intelligence (AI) e-innovation adoption.*

#### 2.1.4 Perceived trialability

Perceived trialability is the extent to which an innovation is on trial for a limited time before adoption (Rogers, 2003, p. 258). The benefits of e-innovation technology may be traced back to their capacity for pre-adoption testing (Christiansen *et al.*, 2022). Likewise, the testing phase increases the likelihood that an organization will successfully accept an innovation before its real deployment (Lin & Chen, 2012). Many studies have found that perceived trialability has a positive impact on e-innovation. Examples include; Yemen's banking sector (e-banking services) (Mutahar *et al.*, 2016), Taiwan's government sector (e-governance services, i.e. tax filing system) (Liang & Lu, 2013), Taiwan's education sector (Open Source Learning Platform) (C.Y. Huang *et al.*, 2020) and Taiwan's corporate sector (e-learning system) (Lee *et al.*, 2011). Chen's (2009) finding indicated that perceived trialability had an insignificant influence on e-innovation (e-learning). At the same time, Ramayah *et al.* (2013) found that perceived trialability negatively affected e-innovation in SMEs in Malaysia. According to the authors, testing a new technology could sometimes be difficult, costing extra time or money. This situation meant allowing technology trials before fully adopting and implementing an innovation might be more expensive. The studies applied the diffusion of innovation theory and the "technology adoption model" and found that perceived trialability directly impacted e-innovation (C.Y. Huang *et al.*, 2020; Lee *et al.*, 2011). Therefore, the following hypothesis was proposed:

**H1D:** *Perceived trialability directly affects artificial intelligence (AI) e-innovation adoption.*

### *2.1.5 Perceived observability*

Perceived observability is well-defined as the extent to which the outcomes of innovations can be visible (seen) to others (Rogers, 2003, p. 258). Perceived observability positively affects the adoption of e-innovation (Rehman & Rajkumar, 2022). Likewise, firms will be more motivated to adopt new technology if it gives visible (observable) benefits similar to those gained by other firms (Badi *et al.*, 2021). Many studies have shown that perceived observability had a positive and statistically significant effect on AI e-innovation (M.P. Chen, 2009; M.H. Huang & Rust, 2013; Ramayah *et al.*, 2013). On the other hand, Liang & Lu (2013) and Wang *et al.* (2018) found an insignificant influence of perceived observability on AI e-innovation. Examining the manufacturing and manufacturing-related services SMEs of Malaysia employing the partial least squares (PLS) technique through the SmartPLS 2.0 software and analysis revealed that innovation characteristics, i.e., perceived observability, was positively related to adopting a technology (Ramayah *et al.*, 2013). Similarly, Huang *et al.* (2020) employed Partial Least Squares Structural Equation Modelling on a sample of 340 respondents in the education sector of Taiwan and found that perceived observability was positively related to e-innovative open source learning platforms supported by diffusion of innovation theory and the technology acceptance model (TAM). As a result, the following hypothesis was proposed:

**H1E:** *Perceived observability positively influences artificial intelligence (AI) e-innovation adoption.*

### *2.1.6 Perceived ease of use and Perceived usefulness (TAM)*

Perceived ease of use is demonstrated by the skills the adopter acquires while using e-innovation. Perceived ease of use is the ability users gain from using e-innovation technology, and their ability to participate in self-directed learning shows how easy it is to use (Al Kurdi *et al.*, 2020). E-innovations' perceived usefulness in the public sector may improve users' learning and save time (Al Kurdi *et al.*, 2020; Soomro, 2018). Similarly, acceptance of e-innovation technology is influenced by perceptions of ease of use and usefulness (Al-Maroof *et al.*, 2021). Several studies have found that useful and easy to use (TAM) significantly affected e-innovation adoption in different fields (Abdullah *et al.*, 2016; Alsabawy *et al.*, 2016; Ashraf *et al.*, 2016; Carter, 2008; Hamid *et al.*, 2016). According to Abdullah *et al.* (2016), perceived usefulness and ease of use positively and significantly influenced e-innovative portfolios using the AMOS software application. A sample of 242 UK undergraduate students (Alsabawy *et al.*, 2016) found a similar relationship between TAM and e-learning in the Australian education sector. Furthermore, Ashraf *et al.* (2016) revealed that perceived usefulness and perceived ease of use mediated the effects of fit on consumers' attitudes and intentions to purchase from a website using two different samples (i.e., students and actual shoppers) of online shoppers. Therefore, the following hypotheses were proposed:

**H1F:** *Perceived ease of use positively influences the adoption of artificial intelligence (AI) e-innovation.*

**H1G:** *Perceived usefulness positively influences artificial intelligence (AI) e-innovation adoption.*

## *2.2 Employees and e-innovation adoption*

According to Siyal *et al.* (2021), employees must be well-trained and skilled to perform a continuous flow of innovation and achieve the objectives and goals of the private and public sectors. Based on the Self-Determination Theory (SDT), a person has three basic psychological needs: 1. Autonomy, 2. Competence, and 3. Relatedness (Chiu, 2018; Gagné & Deci, 2005; Koe & Sakir, 2020; Ryan & Deci, 2000), where different social and environmental factors can improve or weaken those needs (Chiu, 2018). The e-innovation adoption rate is strongly related to employees' enthused dynamics; intrinsic motivation, extrinsic motivation (Siyal *et al.*, 2021) and perceived self-efficacy (Fuchs *et al.*, 2019).

### *2.2.1 Intrinsic motivation*

A person with a higher degree of intrinsic motivation looks for internal rewards, such as; joy, achievement, or pride (Chiu, 2018; Gagné & Deci, 2005; Ryan & Deci, 2000). However, adopting e-innovation can be difficult and thrilling because e-innovation is completely new to the adopters (Rogers, 2003). Thus, intrinsic motivation is positively and directly related to openness, which means that individuals are interested in and accept e-innovation's novelty (Chiu, 2018; Robbins & Judge, 2015). Similarly, fundamental psychological needs, such as; autonomy, competence, and relatedness, directly influence the intrinsic motivation of entrepreneurs in developing nations like Malaysia to use e-commerce (Koe & Sakir, 2020). In addition, the authors highlighted that one of the ways that might lead to fulfilling intrinsic motivation is by offering options and acknowledging emotions. It follows that when people have a sense of control over their environment, they are more likely to be motivated by internal factors and fully immersed in what they're doing. Several studies have found that intrinsic motivation positively and significantly impacted e-innovation adoption in different sectors. The sectors included; e-commerce (Chen *et al.*, 2019; Koe & Sakir, 2020), social media in the government sector (Demircioglu & Chen, 2019), sharing commercial content on social networking services of e-businesses (Vilnai-Yavetz & Levina, 2018) and e-learning in the education sector (Fırat *et al.*, 2018; Harandi, 2015). Hence, the following hypothesis was proposed:

**H$_{2A}$:** *Intrinsic motivation positively influences artificial intelligence (AI) e-innovation adoption.*

### *2.2.2 Extrinsic motivation*

Several studies found that extrinsic motivation significantly influenced e-innovation technology. Examples include; the education sector (I.F. Liu & Young, 2017), the manufacturing industry (Chiu, 2018) in Taiwan, e-business users (Vilnai-Yavetz & Levina, 2018), mobile shopping using mobile retail applications in China (De Canio *et al.*, 2022) and e-commerce users in Australia (Xuequn Wang *et al.*, 2019). Individuals with high extrinsic motivation strive for external rewards, for instance, money (monetary) gain, recognition from others, or job-related promotion (Chiu, 2018; Gagné & Deci, 2005; Ryan & Deci, 2000). In addition, extrinsically motivated individuals may perform certain tasks for reasons beyond the tasks themselves, such as; reward or recognition (Chiu, 2018; Gagné & Deci, 2005). Besides, individuals with extrinsic motivation might pursue ego goals, comparing themselves with others, leading them to adopt new e-innovations to feel superior (Chiu, 2018). According to Wang *et al.* (2019), the extrinsic motivation among users of e-innovative social commerce positively influenced their contributions to social commerce information and the successful adoption of e-vendor platforms. Similarly, extrinsic motivation in general and monetary incentives, in particular, influenced the sharing of e-business material on social networking sites, which the crowding-out effect may describe, i.e., recycling, information sharing, and sustainable behaviour (Vilnai-Yavetz & Levina, 2018). Extrinsic factors influenced the decision to purchase while using an e-innovative mobile retail application at every stage of the buying process (De Canio *et al.*, 2022). Therefore, the following hypothesis was proposed:

**H$_{2B}$:** *Extrinsic motivation positively influences artificial intelligence (AI) e-innovation adoption.*

### *2.2.3 Self-efficacy*

Self-efficacy implies an individual's belief in their ability to succeed in a particular situation (Bandura, 1977; Fuchs *et al.*, 2019; Raeder *et al.*, 2019). The key predictor of the behaviour of individuals is that they are more likely to become involved in a task if they see themselves as capable of achieving it (Fuchs *et al.*, 2019). Individuals with optimistic self-efficacy tend to accept and adopt e-innovation (Fuchs *et al.*, 2019). Previous research has found that Self-Efficacy (SE) has played an important role in explaining the adoption of AI e-innovative e-technologies or systems (Ahmad *et al.*, 2023; Brown *et al.*, 2006; Park *et al.*, 2012). Considering the TAM model, Alalwan *et al.* (2017) discovered that self-efficacy favoured adopting e-innovative technology, such as; e-banking services in Jordan. Many studies have indicated that self-efficacy had insignificant effects on adopting e-innovation technologies. Examples include; e-government services in Taiwan (Liang & Lu, 2013), e-portfolios in the education sector of the UK (Abdullah *et al.*, 2016), open-source learning platforms (Huang *et al.*, 2020), and online academic help-seeking (Fan & Lin, 2023) in the education sector of Taiwan. Thus, the following hypothesis was proposed:

**H$_{2C}$:** *Self-efficacy significantly influences artificial intelligence (AI) e-innovation adoption.*

## 3. Methodology

### *3.1 The study model*

Based on the previous discussions in the existing literature, this study's model was drawn, as seen in Fig. 1.

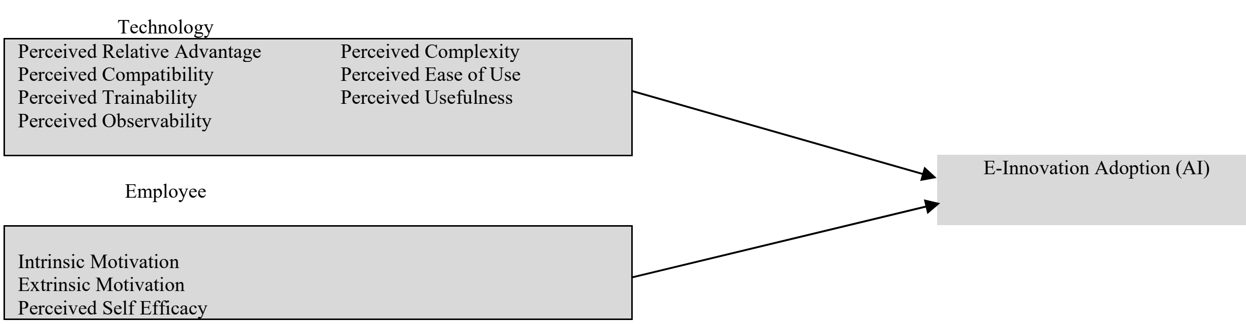


**Fig. 1.** The proposed method

*3.2 Method*

The present study chose the IBM SPSS Statistics and Amos V. 28 software applications for data analysis. First, the present study generated descriptive and inferential statistics for the sample data. The descriptive statistics explained the mean, minimum, maximum and standard deviation values of the respondent's answers to the questionnaire variables. Second, the inferential statistics tested the construct reliability and validity and were used to examine the measurement model. The alpha coefficients of Cronbach were tested to determine the reliability of each core parameter (construct reliability). Second, Structural Equation Modeling (SEM) was used to test different theoretical models and examine the relationships between those constructs (Alsabawy *et al.*, 2016; Schumacker & Lomax, 2004). Third, the Amos software application was used for regression and path analysis. Finally, for robustness checking, the present study ran a linear regression analysis to identify the direction and significance level of the relationship between the predictors' variables and AI e-innovative adoption. This analysis established which factors had significant relationships when using AI e-innovation in the UAE Government sector. Also, the linear regression assumptions were tested.

*3.3. Selection of the sample and variables*

The research strategy's primary source of data collection was through distributing a quantitative structured survey questionnaire. The sample frame was UAE governmental sectors. The present study sent out 1500 surveys via email and social media to separate government entities and received back 1037 completed surveys. Knowing the true response rate without knowing how many surveys were sent out was impossible.

Furthermore, the present study elected to maintain the anonymity of the questionnaire's respondents; nevertheless, it was aware of the identities of the participating businesses but will not disclose them. Rather, the present study has provided a comprehensive report on the findings. The following equation explains the variables of the questionnaire:

$$INO_i = \alpha_0 + \alpha_1 PRA_1 + \alpha_2 PCO_2 + \alpha_3 PNC_3 + \alpha_4 PTR_4 + \alpha_5 PEU_5 + \alpha_6 PUS_6 + \alpha_7 POB_7 + \alpha_8 EXM_8 + \alpha_9 INM_9 + \alpha_{10} PSE_{10} + \varepsilon_i$$

The endogenous variable was AI e-innovation adoption (INO). In contrast, the proxies of technology were; Perceived relative advantage (PRA), Perceived compatibility (PCO), Perceived non-complexity (PNC), Perceived trialability (PTR), Perceived Ease of Use (PEU), Perceived Usefulness (PUS), Perceived observability (POB). Similarly, the sub-factors of employees were Extrinsic Motivation (EXM), Intrinsic Motivation (INM), and Perceived Self-efficacy (PSE).

## 4. Empirical Results

*4.1 Descriptive analysis*

Table 1 presents each study parameter's mean, minimum, maximum, and standard deviation values. The participants revealed their opinions regarding various factors, such as; employee and technological influences on AI e-innovation adoption. The opinions were evaluated using a 5-point Likert scale. The accessibility score showed high results, with a mean of 3.775 and a 0.8693 standard deviation.

Table 1
Descriptive Statistics:

| Variables | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|
| FA_PRA | 1.00 | 5.00 | 3.583 | .8438 |
| FA_PCO | 1.00 | 5.00 | 3.653 | .8601 |
| FA_PNC | 1.00 | 5.00 | 3.605 | .8578 |
| FA_PEU | 1.00 | 5.00 | 3.665 | .8519 |
| FA_PUS | 1.00 | 5.00 | 3.733 | .8693 |
| FA_POB | 1.00 | 5.00 | 3.686 | .8423 |
| FA_EXM | 1.00 | 5.00 | 3.718 | .8595 |
| FA_INM | 1.00 | 5.00 | 3.775 | .8478 |
| FA_PSE | 1.00 | 5.00 | 3.702 | .8493 |
| FA_PTR | 1.00 | 5.00 | 3.668 | .8501 |
| DE_INO | 1.00 | 5.00 | 3.692 | .7793 |

*4.2 Measurement Model Assessment (Appendix A)*

Construct reliability and validity were utilized to analyze the measurement model. The alpha coefficients of Cronbach were examined to establish the reliability of each key parameter (construct reliability). In this investigation, all of the individual alpha coefficients of Cronbach varied from 0.700 to 0.907, exceeding the suggested value of 0.7 (Kannan, 2005). The sub-factors of technology represented an acceptable level of reliability as follows: Perceived relative advantage (PRA) $a = 0.881$, Perceived compatibility (PCO), $a = 0.889$ Perceived non-complexity (PNC), $a = 0.871$, Perceived trialability (PTR), $a = 0.87$, Perceived Ease of Use (PEU), $a = 0.895$, Perceived Usefulness (PUS), $a = 0.92$ and, Perceived observability (POB), $a = 0.88$.

Similarly, the sub-factors of employees indicated an adequate level of reliability, as follows; Extrinsic Motivation (EXM), *a* = 0.891, Intrinsic Motivation (INM), *a* = 0.893, and, Perceived Self-efficacy (PSE), *a* = 0.891. Finally, the total reliability indicated *a* = 0.983, and the total variance explained was 70.612, suitable for further analysis.

### *4.3 Goodness of Fit measure (Table 2)*

Structural Equation Modeling (SEM) was implemented to validate various theoretical models and investigate the connections between the structures (Alsabawy *et al.*, 2016; Schumacker & Lomax, 2004). In this particular investigation, the cut-offs for indices proposed by Bagozzi & Yi (2012) were utilized. The following table presents the proposed cut-off thresholds for the standardized root-mean-square residual (SRMR), non-normed fit index (NNFI), and comparative fit index (CFI) for the fitness model to continue with further analysis. Absolute fit indices were determined using the goodness-of-fit index (GFI) and the adjusted goodness-of-fit index (AGFI).

In this investigation, the cut-offs for the GFI and AGFI satisfied the model's requirements (Alsabawy *et al.*, 2016). (RMR) and Standardized Root Mean-Square Residual (SRMR) values are utilized to determine the absolute fitness of a model. A number near zero suggests that the RMR is a good fit, whereas a high value (close to 1) indicates that the RMR is a poor fit. This rule of thumb was employed in this study for the RMR (Kline, 2015).

**Table 2**
Fit indices for the model goodness of fit measure:

| Goodness of Fit measure | Recommended value | Actual value |
|---|---|---|
| $\chi 2$ /df | ≥3.00 | 10.65 |
| GFI | ≥0.90 | .921 |
| IFI | ≥0.90 | .973 |
| NFI | ≥0.95 | .970 |
| CFI | ≥0.90 | .973 |
| RMSEA | ≤0.08 | .097 |
| AGFI | ≥0.90 | .900 |
| SRMR | ≤0.90 | .015 |

$X^2$= 447.38; d.f. = 42; GFI = .921; IFI = .973; NFI = .970; CFI = .973; RMSEA = 0.97; AGFI = .900; SRMR =.015.

**Table 3**
Amos Regression Analysis:

| Varia- | | | **Estimate** | **S.E.** | **C.R.** | **P** |
|---|---|---|---|---|---|---|
| FA_PRA | ← | Technology | 1.000 | | | |
| FA_PCO | ← | Technology | 1.038 | .026 | 39.518 | *** |
| FA_PNC | ← | Technology | 1.033 | .026 | 39.354 | *** |
| FA_PEU | ← | Technology | 1.041 | .026 | 40.583 | *** |
| FA_PUS | ← | Technology | 1.081 | .026 | 42.057 | *** |
| FA_POB | ← | Technology | 1.027 | .025 | 40.411 | *** |
| FA_PTR | ← | Technology | 1.008 | .026 | 38.198 | *** |
| FA_EXM | ← | Employee | 1.000 | | | |
| FA_INM | ← | Employee | .968 | .019 | 50.536 | *** |
| FA_PSE | ← | Employee | .941 | .020 | 46.333 | *** |
| DE_INO | ← | Technology | .776 | .028 | 27.468 | *** |
| DE_INO | ← | Employee | .274 | .023 | 11.929 | *** |

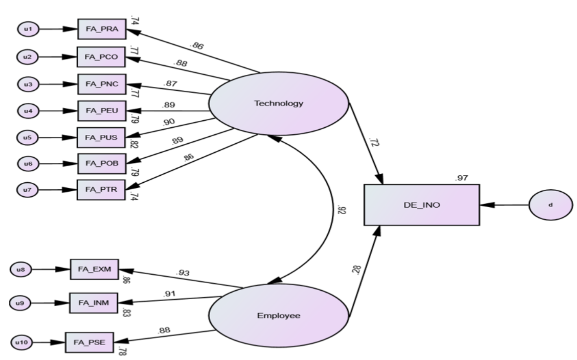


**Fig. 2.** AMOS results.

### *4.4 Inferential Statistics results*

As can be seen in Table 3, all the hypotheses were supported. All technological proxies indicated a favorable and statistically significant effect on adopting AI e-innovation technology. This outcome was consistent with the findings of; Abdullah *et al.*, 2016; Achjari & Quaddus, 2003; Ali Abbasi *et al.*, 2022; Alsabawy *et al.*, 2016; Ashraf *et al.*, 2016; Carter, 2008; Chatterjee *et al.*, 2021; Hamid *et al.*, 2016; Hoang & Nguyen, 2022; Liang & Lu, 2013; Mutahar *et al.*, 2016; Pillai *et al.*, 2021; Poong *et al.*, 2009; Ramayah *et al.*, 2013. Second, all employee proxies revealed a positive and significant effect on AI e-innovation technology adoption, which was in line with the results of; Chiu, 2018; De Canio *et al.*, 2022; I.-F. Liu & Young, 2017; Vilnai-Yavetz & Levina, 2018; Xuequn Wang *et al.*, 2019.

## 5. Discussion

The present study aimed to investigate the effect of technology and employees on AI e-innovation adoption in the UAE. The UAE is the regional leader in innovation in areas such as; smart economy, artificial intelligence (AI) and human capital (Khan, 2019). In support of this study's hypotheses, several reasons were considered. First, it is true that one's ability to appreciate innovation's worth increases when one gains exposure to it through various means, including; firsthand participation (Achjari & Quaddus, 2003). Additionally, practicality is a "function of the match between an invention and one's desired work style" (Achjari & Quaddus, 2003; Agarwal & Karahanna, 1998). Second, an invention is more likely to be widely used due to increased appeal. It is quite probable that government entities would use technology if they could see the benefits of doing so. When small and medium-sized businesses see that technology initiatives launched by larger corporations are fruitful, they have been more likely to implement similar projects themselves (Ramayah *et al.*, 2013). Third, it seems to be reasonable that companies would treat customer feedback seriously and work hard to meet the needs of their clientele in a highly competitive market such as the UAE. Fourth, people are more likely to accept and embrace a novel service if they can first try it out, understand its benefits, learn how easy it is to use, and see how well it meets their needs. Fifth, users are more inclined to stick with an AI innovative service, such as e-government services if they believe that they will enhance their interactions with government agencies. Since such systems are user-facing, the designer must consider the user's requirements.

Regarding employees' behavior toward adopting AI innovation, some were only driven by external rewards, such as the admiration of others. As a result, they may have adopted new e-innovations to boost their sense of self-importance through comparison (Liu, 2020). Where people were more likely to be intrinsically driven and engrossed in what they were doing when they felt they had some say over their surroundings. Besides, one of the most important factors in determining how someone would act was whether they believed they had the skills necessary to carry out tasks (Fuchs *et al.*, 2019). Similarly, the authors mentioned that e-innovation was more likely to be accepted and adopted by those with high self-efficacy (Fuchs *et al.*, 2019).

## 6. Conclusion

This study examined factors, such as technology and employee influence on AI adoption of e-innovation in the United Arab Emirates. This study tried to reveal the success or failure of e-innovation adoption in the public sector of the UAE and hinted at potential e-innovative projects to consider essential factors before adopting it. The study's sample covered the government sector, and the data collection method was a survey questionnaire with a sample size of 1037 responses comprising government employees. Besides, this paper was mainly built on the diffusion of innovation and technology acceptance theories. The analysis findings showed that technology (an external factor) positively contributed greatly to adopting AI e-innovation technology. Further analysis revealed that employee (internal factor) proxies directly influenced the adoption of AI e-innovation technology. Overall, internal and external factors contributed to adopting e-innovation in the United Arab Emirates. Researchers, developers, and practitioners in the public sector will find the results of this study of special interest as they contribute to a better understanding of how people may respond to the introduction of novel AI technologies. Additional market-related elements should be examined for future study directions to investigate their potential significance.

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**Appendix A: Measurement Model Assessment**

| | Factor loadings | Reliability | Variance Explained |
|---|---|---|---|
| ***Technology*** | | | |
| ***Perceived relative advantage (PRA)*** | | ***0.881*** | |
| PRA-1 | 0.646 | | |
| PRA-2 | 0.660 | | |
| PRA-3 | 0.655 | | |
| PRA-4 | 0.618 | | |
| PRA-5 | 0.588 | | |
| PRA-6 | 0.579 | | |
| ***Perceived compatibility (PCO)*** | | ***0.889*** | |
| PCO-1 | 0.632 | | |
| PCO-2 | 0.655 | | |
| PCO-3 | 0.652 | | |
| PCO-4 | 0.592 | | |
| PCO-5 | 0.560 | | |
| ***Perceived non-complexity (PNC)*** | | **0.871** | |
| PNC-1 | 0.662 | | |
| PNC-2 | 0.664 | | |
| PNC-3 | 0.565 | | |
| PNC-4 | 0.567 | | |
| PNC-5 | 0.413 | | |
| ***Perceived trialability (PTR)*** | | **0.870** | |
| PTR-1 | 0.447 | | |
| PTR-2 | 0.462 | | |
| PTR-3 | 0.467 | | |
| PTR-4 | 0.425 | | |
| PTR-5 | 0.421 | | |
| ***Perceived Ease of Use (PEU)*** | | **0.895** | |
| PEU-1 | 0.479 | | |
| PEU-2 | 0.505 | | |

| | | | |
|---|---|---|---|
| PEU-3 | 0.456 | | |
| PEU-4 | 0.460 | | |
| PEU-5 | 0.463 | | |
| ***Perceived Usefulness (PUS)*** | | **0.92** | |
| PUS-1 | 0.574 | | |
| PUS-2 | 0.622 | | |
| PUS-3 | 0.614 | | |
| PUS-4 | 0.608 | | |
| PUS-5 | 0.645 | | |
| PUS-6 | 0.605 | | |
| ***Perceived observability (POB)*** | | **0.88** | |
| POB-1 | 0.525 | | |
| POB-2 | 0.497 | | |
| POB-3 | 0.513 | | |
| POB-4 | 0.494 | | |
| POB-5 | 0.559 | | |
| ***Employee*** | | | |
| ***Extrinsic Motivation (EXM)*** | | ***0.891*** | |
| EXM-1 | 0.501 | | |
| EXM-2 | 0.563 | | |
| EXM-3 | 0.612 | | |
| EXM-4 | 0.607 | | |
| EXM-5 | 0.636 | | |
| ***Intrinsic Motivation (INM)*** | | **0.893** | |
| INM-1 | 0.627 | | |
| INM-2 | 0.592 | | |
| INM-3 | 0.660 | | |
| INM-4 | 0.682 | | |
| INM-5 | 0.678 | | |
| ***Perceived Self-efficacy (PSE)*** | | **0.891** | |
| PSE-1 | 0.645 | | |
| PSE-2 | 0.707 | | |
| PSE-3 | 0.639 | | |
| PSE-4 | 0.688 | | |
| PSE-5 | 0.636 | | |
| | | Overall Reliability = 0.983 | Overall Variance = 70.612 |

## Appendix B

Linear Regression Results (SPSS):

| Variables | Unstandardized Coefficients | | Standardized Coefficients | Sig. | Collinearity Statistics | | R square | Adjusted R square | Durbin Watson |
|---|---|---|---|---|---|---|---|---|---|
| | B | Std. Error | Beta | | Tolerance | VIF | | | |
| (Constant) | 0.001 | 0.027 | | 0.970 | | | | | |
| FA_PRA | 0.102 | 0.012 | 0.110 | 0.000 | 0.263 | 3.809 | | | |
| FA_PCO | 0.127 | 0.013 | 0.140 | 0.000 | 0.242 | 4.133 | | | |
| FA_PNC | 0.145 | 0.012 | 0.159 | 0.000 | 0.266 | 3.763 | | | |
| FA_PEU | 0.088 | 0.013 | 0.096 | 0.000 | 0.220 | 4.540 | | | |
| FA_PUS | 0.126 | 0.014 | 0.140 | 0.000 | 0.198 | 5.051 | | | |
| FA_POB | 0.105 | 0.013 | 0.114 | 0.000 | 0.226 | 4.420 | | | |
| FA_EXM | 0.143 | 0.014 | 0.158 | 0.000 | 0.197 | 5.074 | | | |
| FA_INM | 0.074 | 0.013 | 0.081 | 0.000 | 0.220 | 4.552 | | | |
| FA_PSE | 0.095 | 0.012 | 0.104 | 0.000 | 0.270 | 3.711 | | | |
| | | | | | | | 0.801 | 0.795 | 1.827 |