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Mediation Model of Service Quality and Behavioural Intention to Use of Artificial Intelligence Security Technology in UAE

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Abstract: This study created and evaluated a mediation model which allows the role of essential artificial intelligence (AI) in mediating the connection between service quality and behavioural intent to use AI security features in the United Arab Emirates. The primary objective is to improve the standards for customer service in the UAE's artificial intelligence security industry. The data to developed the model was derived from 389 valid questionnaires form the questionnaire survey. The data was screened and cleaned before uploaded in Smart-PLS software to developing and assessing the model. Based on the assessment on the model, it was found that the most fundamental form of artificial intelligence exerts a mediating effect to some extent, on the connection that exists between service quality and behavioural intention in terms of the application of Al security technology. The coefficient and t-value point to a substantial indirect relationship between the quality of the service and the intention to use artificial intelligence. This relationship is shown to be indirect rather than direct. It is possible to draw the conclusion that improved service quality raises people's likelihood of intending to use AI security technologies. This is due to the fact that the contribution of such technologies to improved job performance, as well as the convenience with which such technologies can be utilised, raises people's awareness of the perceived value of such technologies.

Keywords: Artificial intelligence, service quality, behavioural intention, SEM, UAE

1. Introduction

Visitors and foreign nationals travel in droves to the UAE, particularly to Dubai and Abu Dhabi. Visitors are drawn to the nation not only for its opulent hotels, expansive malls, and pleasant weather, but also for the safety and security it offers. Crimes like burglaries, robberies, and residential break-ins are extremely uncommon in the United Arab Emirates, and according to previous crime report statistics, about half of all significant crimes are the result of outdated security measures. Additionally, cybercrime is on the rise, with computer hacking increasing by 300 percent in just six months in 2014. Analysts have identified the United Arab Emirates as one of the ten nations which are most susceptible to cyber-attacks (Ammar et al., 2015).

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Despite the advantages of security technologies, there are a number of issues and worries that arise in AI networks, including the possibility of technology abuse due to technical shortcomings and gaps in security systems (Pan, 2016). Additionally, users of AI security technologies might not be happy with using them because fraud signals are transferred by malicious programmes used by criminals to lessen the effectiveness and efficiency of AI systems' communication channels and technologies, which makes it harder for hackers to perform data breaches (Pesapane et al., 2018).Such concerns with AI security system have an impact on employees' job performance and satisfaction with security technologies (Abubakar, 2019).

Additionally, when consumers have negative experiences, e-service quality factors like effort expectation and performance expectancy may negatively affect consumers' intentions to adopt these technologies, like AI security solutions (Chen, & Ko, 2016). Previous studies have shown that many people are reluctant to adopt such technology because they are unhappy with the results (Almarashdeh, 2018). Users' dissatisfaction with technologies as a result of their poor performance and complexity of use has a negative impact on their behavioural intention or readiness to use technologies in the future (Rehman, & Shaikh, 2020). Additionally, users' desire to use AI security technologies would decrease in the future if they did not make their jobs easier due to the fact that they did not enhance work performance (Fragoso, & Espinoza, 2017). Because of the difficulty of use, lack of support for job performance, and inability to meet expectations, employees' dissatisfaction with AI security technologies has a negative effect on their intention to use them in the future.With regard to balancing the world's superpowers and maintaining its security in the future, the UAE will face challenges related to its geographic scope and military's ability to employ modern technology. However, there are few empirical studies on the service quality (SQ) of artificial intelligence (AI) used by government agencies in the United Arab Emirates to safeguard properties (Salih et al., 2017) and effectiveness of AI services available in the United Arab Emirates (Vilhena et al., 2017).

Since the UAE government is responsible for ensuring the safety of the general public's lives and property, the quality of the services must satisfy customer needs. The management of the public organisation must let the public know how they felt about the service quality of the AI technology used to secure facilities in the United Arab Emirates. The management's decision and growth strategy for the relevant AI security technologies will be informed through a survey. There is a absence of research on the SQ of AI in protecting properties in the United Arab Emirates that would be useful to stakeholders, particularly the general public (Salih et al., 2017, Ammar et al., 2015). Thus, the goal of this study is to establish a link between service quality performance and a person's inclination to use AI security technology. In addition, measuring service quality technologies is a difficult task because they are constantly evolving and developing, necessitating ongoing research in this field (Fragoso et al., 2017). This demonstrates the possibility of new findings, particularly when applying novel constructs. The main gap in this study is the use of AI technology needs as a mediator. This paper studied intention to use AI security technologies to improve service quality because this topic is evolving with the appearance of new technologies.

2. Literature Review

2.1 Needs of Artificial Intelligence Technology

Historically, service providers have been people, but as advanced digital technology, particularly artificial intelligence (AI) technologies are increasingly replacing workers to provide contactless services (Huang & Rust 2018). AI is a useful and widely used technology. It enables a device to recognise its environment and make the right choices (Almarashda et al. 2022). AI services are now very beneficial to a variety of businesses, including hotels, shops, restaurants, airports, and general organisations (Chiang, & Trimi, 2020).With the rapid development of artificial intelligence, service technologies provide governments with unmatched opportunities to expand public services and strengthen their engagement with the public because they enable users to access services that are largely independent of the intervention of direct service employees (Bock, et al. 2020). AI technologies have the potential to increase work efficiency, lower service costs, and relieve human workloads, which in turn improve service quality, government and private organisations are using them at an accelerated rate (Chen et al. 2020).

In order to achieve and maintain the anticipated long-term AI benefits, it is crucial to make sure that AI technologies provide pleasant user experiences for all niche user groups (Chen, et al., 2020). Numerous empirical studies have demonstrated that people now place more trust in organisations' successful, cost-free, and responsible services (Pan et al. 2020). Utilizing AI technologies in business operations also somewhat reduces the need for human intervention while increasing accuracy and equity. Because people can now access timely and personalised information and services, the standards of accountability and quality have also increased (Fukuda, 2020). Therefore, AI technologies are developing to meet people's needs for managing their businesses and to simplify organisational processes so that users can be happy with these technologies and interested in future AI security technologies. The current state of various industries demonstrates the need for developing AI technologies, such as AI security technologies, as their use demonstrates an improvement in service quality. Such technologies have the potential to increase work efficiency and accuracy. Therefore, as AI security technology develops, human needs for these technologies serve as the primary impetus for their development. As AI technology advances and user demands rise, it becomes clear that there is a need for ongoing research into the requirements for and applications of AI security technology.

2.2 Behavioural Intention To Use

The term "behavioural intention to use" was coined by Venkatesh et al. (2003) in reference to their Unified Theory of Acceptance and Use of Technology (UTAUT) model. The parameters of performance expectancy, effort expectancy, social influence, and facilitating condition are utilised in this theory in order to investigate users' willingness to use technology in the future. The first factor is performance expectancy, which measures how much a person thinks using a certain technology will help him perform his job better. The second factor, effort expectancy, measures how simple it is to use the available technologies. Effort expectancyhas a stronger impact on behavioural intention to adopt emerging technology systems. The third factor, social influence, is the result of how other people persuade users to use particular systems or cutting-edge technologies. The user's perception that the infrastructure and organisation are in place to support using technologies is the fourth factor, and it is referred to as the facilitating condition.

Several studies have looked into behavioural intention to use these variable for studying behavioural intention of the people. For example, Alrawashdeh et al. (2012) assessed information technology innovation of entrepreneurs, Cheng et al. (2011) carried on research into the use of mobile devices for e - learning, and Mei-Ying et al. (2012) focused their research on the use of e-ticketing by passengers travelling by train in Taiwan. using AI technologies and behavioural intention to use such techniques. Similarly, Shang and Wu's (2017) study on mobile shopping, Rahman and Hoque's (2018) study on telemedicine adoption, Dhiman et al. (2019) study on smartphone fitness app adoption, Alam et al. (2020) study on health services, Tam et al. (2020), study on customer satisfaction have focused on studying behavioural intention to use the AI.These studies looked at technology use from various angles, and they made the case that factors of technology adoption intention can be used to better understand user psychology. The results, however, may be distinctly or barely different from study to study and from one context to another, so they are not consistent across all studies. These unpredictable findings of the performance expectation, effort expectation, social influence, and spatial arrangements indicate the need for future investigations on behavioural intentions regarding the use of AI security technologies.

3. Service Quality Models

Higher education institutions must conduct thorough and accurate research and measure the effectiveness of their services because it is a crucial component. As already mentioned, a variety of factors influence service quality (Meesala & Paul, 2018). Customers' preferences, teacher effectiveness ratings, and course completion rates are all important factors in determining a company's credibility. Additionally, it influences students' decisions to transfer between institutions. Given the importance of these issues, many businesses take them into special consideration when coming up with suggestions to raise the calibre of their services.

3.1 SERVQUAL Model

A key tool for evaluating service qualityis SERVQUAL (Narteh, 2018). Managers and scientists frequently use this instrument to evaluate client expectations for service quality. Regardless of the type of service, consumers evaluate quality using the same metrics (Wu et al. 2018). One establishment can differentiate themselves from their rivals by cultivating a culture that values quality as a source of competitive advantage. Customers are able to evaluate the quality of a service based on the following five criteria: dependability, tangibility, accountability, protection, and empathy (Narteh, 2018). The ability of a business to fulfil its commitments in a responsible and accurate manner is referred to as reliability. Tangibility includes the physical infrastructure, equipment, personnel, and communication tools. It provides prompt services and staff that can help customers in terms of accountability. Employees' politeness and expertise determine their capacity to offer faith and trust. Lastly, empathy is the capacity of one person to comprehend the feelings of another by providing tailored customer service.

Parasuraman et al. (1988) in their study created a method to compare the customers' expectations with their perceptions of quality. When it comes to measuring and analysing service quality, SERVQUAL is a tried-and-true method. The year 1985 marked the publication of SERVQUAL for the first time. There are 22 individual components split evenly between the two segments of the initial SERVQUAL instrument. In the first 22 questions, respondents are asked their thoughts on the overall quality of the services they provide, while in the last 22 questions, respondents are questioned on the results that network operators actually achieve. The disparity between the quality of service as planned and the quality of service as experienced is a representation of the extent of service quality. The 22 items correlate to the five SERVQUAL dimensions that have been defined (service quality dimensions). The purpose of this instrument is to ascertain the degree to which or the degree to which there is a difference between the service user's expectations and perceptions users regarding a specific service.The authors of SERVQUAL refer to service quality as a relationship:

$$Q=P-E$$

Where: E - expectations of service users, measured with 22 statements
P - Perceptions of service users, measured with 22 statements (Armstrong et al. 1997).

Raziei et al. (2018) used SERVQUAL instrument to gauge service users' expectations and to gauge their perceptions and measure the gap, or discrepancy, between those perceptions and those expectations. The authors emphasisedthat the value of the unclear, i.e., uncertain existence of SERVQUAL's expectation obtained by measuring the relationship between various expectations and perceived service quality

3.2 SERVPERF Model

Since its introduction, SERVQUAL has been used in a range of conventional services, including retail businesses (Lupo, 2015), support services, and health care applications (Fragoso & Espinoza, 2017). On the other hand, a number of academics have raised doubts on the usefulness of the gap model when it comes to evaluating the quality of services (Fragoso et al., 2017). Instead of comparing expectations to reality, Cronin and Taylor (1992) proposed SERVPERF. SERVPERF model appraise SERVQUAL model with additional parameters on customer awareness of service quality. This suggests that there is at least some degree of consensus regarding the most important aspects of conventional service quality. Cronin and Taylor (1992) were extremely harsh in their criticism of the role that standards play in determining the quality of services. They argued that SERVQUAL has problems both conceptually and operationally. They put it through its paces in four different service industries, namely quick-service dining, the financial industry, dry cleaning, and pest control, in collaboration with SERVPERF. Their investigation was later reproduced, and the research results of other studies have revealed that empirical facts support the P-E=quality gap's appropriateness as the main criterion of service quality. The SERVPERF scale can be calculated using:

$$SQi=\sum k\ j=1Pij$$

Where SQi =perceived service quality of individual “i”
k – Number of items
p – Perception of individual “i” concerning the performance of a service firm “j”

Brown et al. (1993) created a new indicator of direct output analogies with preconceptions that use the Likert scale as a response to criticisms levelled against the psychometric validity of SERVQUAL. Their defence was based on the fact that no two people can give the same answers to questions about their goals and the outcomes they anticipate, and that despite this, there is a significant correlation between differences in responses and favourable results.

3.3 The Study Conceptual Model

A conceptual framework is a diagram that shows how the study's postulated variables are thought to relate to one another. The theoretical analysis framework describing the linkages and relationships between the study variables is shown in Figure 1.

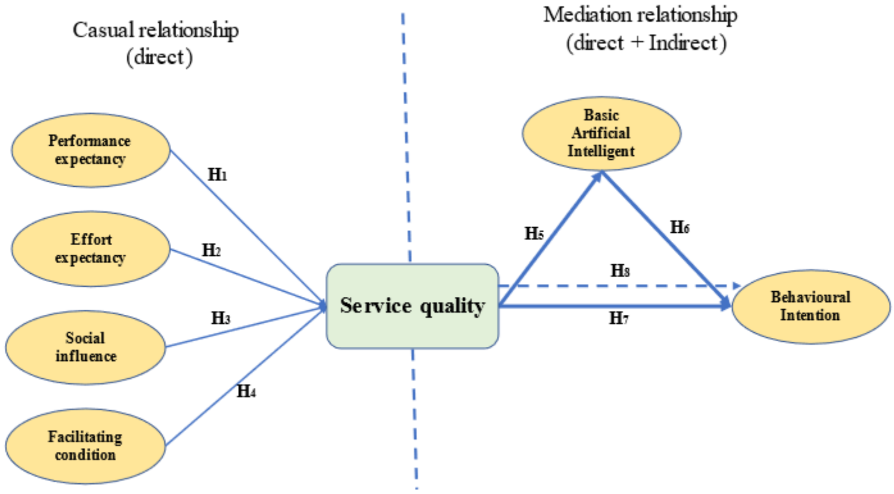

Fig. 1 - Conceptual model of AI security technology in the UAE

This conceptual model asa figure 1 indicates that the model has two structural components where the first component depict a casual relationship amongst the constructs and the second components depict mediation relationship. The constructs/variables of the model are summarised as in table 1.

Table 1 - Constructs/variables in the conceptual model

Independent cosntructs	Act as dependent and also independent construct	Mediator	Dependent construct
i. Performance expectancy ii. Effort expectancy iii. Social influence iv. Facilitating condition	Service Quality	Basic Artificial Intelligent	Behavioural Intention

In the above Figure 1 and Table 1, the independent variables are depicted as success expectancy, effort expectancy, social impact, and facilitating state, respectively developed based on one of the most influential theory of *Unified Theory of Acceptance and Use of Technology* (UTAUT). According to this research, direct predictors of consumption purpose and behaviour include factors such as performance expectations, effort expectations, social impact, and favourable conditions. In the UTAUT, the five factors that predict whether an individual will engage in behaviour for a specific purpose or use are output expectancy, effort expectancy, social impact, and supportive circumstances. The following factors are considered to be predictors, as stated by Venkatesh et al. (2003): Efficiency expectancy is characterised as "the degree to which a person implies that using the system will facilitate him or her in enhancing quality in job performance. Effort expectancy is characterised as "the extent toward which by using system is easy," and social impact is characterised as "the degree to which a person perceives that others consider he or she can use the new system."

In both volunteer and mandatory use settings, the UTAUT model found that the effect of effort expectancy was only significant during the first usage duration of either setting. The more one uses software, the more accustomed they will become to using it, and as a result, the significance of effort-oriented constructions may start to decrease. It is important to take into account a person's level of awareness regarding the viewpoints of others, the subjective culture of their reference group, specific interpersonal agreements with other people, and the degree to which utilising an invention is considered to improve one's appearance or status within their social structure (Singh & Prasher, 2019). The authors believe that future research should focus on more extensively developing and validating reflecting higher for each of the constructs, with a concentrate on content validity, as well as numerous fronts or expanding UTAUT with the new measures, because they agree that practise restrict content validity. In addition, the authors suggest that future research should focus on developing and validating reflecting higher for each of the constructs, with an emphasis on content validity (Baur & Uriona, 2018). In Kano's model, the behavioural intention and the essential requirement for AI technology are both considered to be mediating variables. It is the dependent variable that needs to be improved in order for the relationship between the and independent variables to get better. The implementation of aluminium shielding technology is the dependent variable in this model.

3.4 Conceptual Model Hypothesis

As technology is constantly evolving and developing, new findings and implications may occasionally arise from one service to another and necessitate continuous measurement of service quality (Fragoso et al., 2017). Additionally, the expansion and improvement of the quality of services is facilitated by the quality of e-services, such as effort expectancy and performance expectancy, and this has a favourable impact on the intention to adopt the technology. Consequently, it is assumed that the first compondent of the model:

- **H_1:** Performance expectancy has a significant relationship with the Service quality in the use of AI security technology.
- **H_2:** Effort expectancy has a significant relationship with the Service quality in the use of AI security technology.
- **H_3:** Social influence has a significant relationship with the Service quality in the use of AI security technology.
- **H_4:** Facilitating condition has a significant relationship with the Service quality in the use of AI security technology.

Consequently, it is assumed that the second compondent of the model:

- **H_5:** Service quality has a significant relationship with basic artificial intelligence in the use Al security technology.
- **H_6:** Basic artificial intelligent has a significant relationship with the behavioural intention in the use Al security technology.
- **H_4**: Service quality has a significant relationship with behavioural intention in the use Al security technology.
- **H_8**: Basic artificial intelligent has mediation effect to the relationship between service quality with behavioural intention in the use Al security technology.

Due to prior bad experiences, many people are hesitant to use technology, including AI security technologies (Almarashdeh, 2018), which has a negative impact on their behavioural intention to use AI security technologies. In other words, behavioural intention is a term that describes users' willingness to use technology in the future, which is a crucial sign for the use of AI security in the future (Rehman, & Shaikh, 2020). Users anticipate that technologies, like AI security technologies, will make their jobs easier. Employee satisfaction suffers when AI security technologies do not enhance job performance, which has a negative impact on how they use technology (Fragoso et al., 2017). Technology is anticipated to contribute to the expansion and improvement of services, while subpar technology services have a detrimental impact on the use of these technologies in the future. Because these technologies can help to improve their work, which raises the behavioural intention to use AI security technologies, they can play a mediating role in assisting service quality performance (Almarashdeh, 2018). As a result, employees will have the intention to adopt technologies that make their jobs easier, whereas the behavioural intention to use AI security technologies may increase when they support service quality performance.

4. Research Methodology

This study used a quantitative approach to address its research questions (Creswell, 2013). In order to find and verify a set of stochastic direct causal laws that can be employed to predict broad trends in human activity, the quantitative method is a systematic method that combines deductive reasoning with in-depth observational data of individual behaviour (Creswell, 2013; Punch, 2013). By gathering systematic data from a sizable sample group and extrapolating the findings to the entire population, quantitative approach can quantify certain characteristics (Creswell, 2013). The experimental nature of this study validates the use of numerical techniques to investigate and bring to the exterior deeply ingrained employees ' perception for analysis with the goal of understanding audience perceptions, behaviours, and attitudes (Padgett, 2016). This study used a self-administered questionnaire survey to gather its data. Self-administered questionnaires are challenging to use because they depend more on the accuracy of the written word than the interviewers' skills (De Vaus, 2013; Bryman& Bell, 2015). On the other hand, there are several advantages to this form (Creswell, 2013; Davies & Hughes, 2014). Because it involves "selecting a relatively large number of a population's units or specific subsets (strata) of an inhabitants in a random manner where the likelihood of inclusion for each member of the population is determinable," the probability random sampling method was used for sampling (Teddlie & Yu, 2007). A five-point Likert scale was created for the questionnaire in order to collect data.

The United Arab Emirates' Ministry of Interior's operations staff received the questionnaire (UAE). About 17,000 people work in administration in the UAE. The results show that 420 questionnaires (100%) were distributed, and 389 (92.6%) of them were returned. After data cleaning and screening, 359 responses were determined to be valid and usable for further data analysis. The Social Science Statistical Package (SPSS) and SmartPLS software were used to analyse the data and build a structural model. Data assessment is frequently used to determine whether a data distribution is normal (Awang 2014). Indicating non-normality, the distribution of highly skewed or highly kurtosis results suggests that the estimate could be influenced by outside factors. Pallant (2011) proposed a parametrically appropriate symmetry distribution, assuming a regular distribution, with skew and kurtosis values ranging from -1 to +1. Additionally, data analysis methods such as structural equation modelling (SEM) were used to validate relationships between constructs and indicators (Hair et al., 2014). A group of statistical models known as SEM are used to describe and clarify the connections between various latent variables (constructs). SEM allows researchers to simultaneously examine multiple dependent and independent structures' intertwined relationships. SEM analytical techniques have become widely adopted in a variety of fields as a result, and they have established themselves as an essential tool for academic research (Kline, 2015).

5. Development and Assessmen of PLS-SEM Model

The model was developed in SmartPLS software according to the concept model as figure 1. The model was then assessed in two stages where at the first stage was assessed at measurement component level and the second stage was assessed at structural level.

5.1 Assesment at Measurement Level

The assessment is conducted in two approaches where the first approach is to determine the concergent validity and the second approach is to determine the discriminant validity of the model.

5.1.1 Convergent Validity of the Measurement Component

First step of the PLS-SEM analysis the convergent validity assessment of the measurement model. It involves reliability of the indicators as well as the reliability of the constructs. Indicators are evaluated based on the loading value where the indicators with loading of 0.7 and above are considered suitable. Reliability is the extent to which a scale produces accurate and stable measurements over time. Additionally, it demonstrates how the scale is error-free (Pallant, 2011; Creswell, 2014). Despite the fact that Cronbach's alpha is the most widely used reliability indicator (Awang, 2012), composite reliability is preferred when analysing PLS-SEM. The composite dependability needs to be at least 0.7 for the measurement model to be considered reliable (Wong, 2013). To achieve reliability, though, a composite reliability of 0.6 is also thought to be sufficient, especially for recently developed scales. Table 2 displays the measuring models' convergent validity.

Table 2 - Measurement model’s convergent validity

Variables	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Performance Expectancy	0.897	0.804	0.653
Effort Expectancy	0.818	0.834	0.701
Social influence	0.871	0.814	0.68
Facilitates condition	0.828	0.824	0.709
Behavioural intention to use AI	0.802	0.821	0.699
AI Technology Needs	0.807	0.824	0.671
Service quality	0.859	0.812	0.781

The table 2 above displays the convergent validity outcome. The AVE values for the entire construct are higher than 0.5 which is the threshold value for AVE (Rahman et al. 2013). Additionally, the composite reliability can vary between 0 and 1 (Memon et al. 2013). For satisfactory model, Composite Reliability (C.R.) and all Cronbach's Alpha values are higher than 0.7, the optimum value. As a consequence, each measurement model complied with the criterion for convergent validity.

5.1.2 Discriminant Validity of Measurement Component

Measurement model discriminant validity evaluates how distinct a model is from other research constructs. It compares one measurement model to others in the structural model (Memon & Rahman, 2013). Predicated on cross loading criteria, discriminant validity between measurement models is established. In order to satisfy the cross-loading criterion, according to Chin (1998), the items must load more heavily on their underlying constructs than they cross-load on some other constructs (Hair et al., 2014; Wong, 2016). Table 3 displays the outcomes of loading indicator values onto constructs.

Table 3 - Discriminant validity

Indicators	Model variables						
	AITN	BEHIN	EFF	FCON	PERF	SEQUAL	SOCI
AITN1	0.744						
AITN2	0.883						
AITN3	0.641						
AITN4	0.610						
AITN5	0.636						
BEHIN1		0.737					
BEHIN2		0.752					
BEHIN3		0.772					
BEHIN4		0.633					
BEHIN5		0.647					
BEHIN6		0.750					
EFF1			0.744				
EFF2			0.832				
EFF3			0.589				
EFF4			0.627				
EFF5			0.605				
EFF6			0.713				
EFF7			0.856				
FCON1				0.616			
FCON2				0.892			
FCON3				0.516			
FCON4				0.906			
FCON5				0.700			
PER1					0.699		
PER2					0.752		
PER3					0.728		
PER4					0.783		
PER5					0.593		
PER6					0.655		
PER7					0.700		
SEQUA1						0.798	
SEQUA2						0.730	
SEQUA3						0.827	
SEQUA4						0.749	
SEQUA5						0.807	
SOCI1							0.779
SOCI2							0.837
SOCI3							0.849
SOCI4							0.856

In the table 3, the diagonally italicised and bolded values represent the square roots of the measurement models' AVEs. Correlations between measurement models are represented by the values beneath the diagonal. The results revealed that no measurement model has a greater correlation with any other measurement model than the square root of its AVE. As a result, the measurement models met the criterion for discriminant validity.

5.2 Assesment at Structural Level

During the second stage of the PLS-SEM evaluation criteria, the structural (inner) model is examined in depth. The structural model is the one that puts in place the causal connections between the various measurement models (Hair et al., 2014). The connections that are made are planned with the intention of providing answers to research questions and evaluating research hypotheses. The accuracy of a structural model's ability to forecast the behaviour of endogenous components is rated, as is the model's overall quality. Figure 2 presents the structural model of the study.

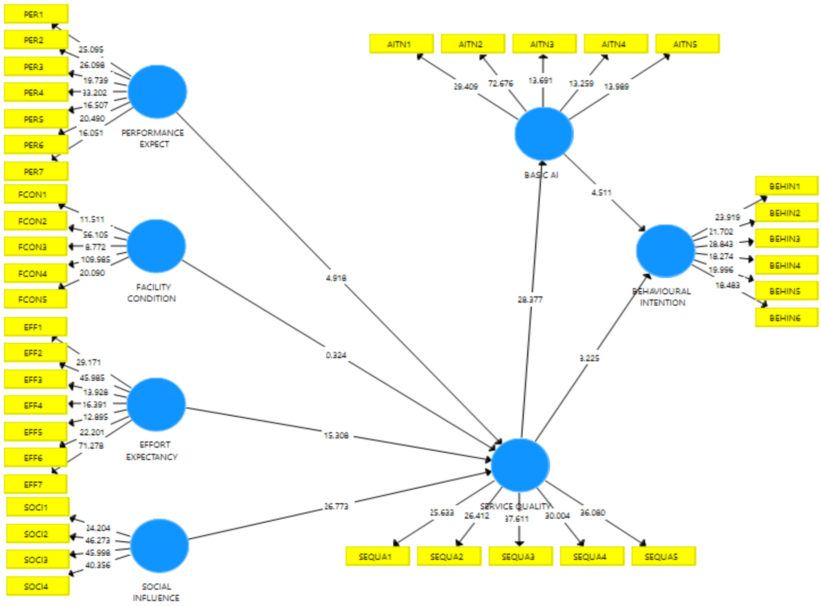

Fig. 2 - Final model showing relationship between the variables

The final model and its t-statistics are shown in the figures above, respectively. Figure 2 displays the path coefficients, the coefficient of determination (R^2), and the t-statistics, which display the significance level. The formulated hypotheses are tested using the data from the structural model.

5.2.1 Coefficient of Determination (R^2) Assessment

The structural model's quality is measured by R^2, which evaluates how much variance the model can explain. The R^2 statistic, also known as the coefficient of determination, displays how much the exogenous constructs contributed overall to the structural model's ability to predict or explain the variance of the endogenous construct. The quality of the model increases with the amount of variance that can be predicted or explained, and vice versa (Wong, 2016). Despite the lack of universal standards for determining what should constitute an acceptable level of R^2, many academics have offered suggestions for what should be acceptable, which can vary from one discipline to another. Hair et al., (2014) and Wong (2016) proposed that R^2 value of 0.25 should be regarded as weak, 0.50 as moderate, and 0.75 as significant. Khahro et al. (2021) cited that Cohen (2013) considers R^2 of 0.26 as substantial. The R^2 levels of the study were evaluated using general guidelines suggested by Hair et al. (2014). Table 4 below provides the R^2 for the final model.

Table 4 - R^2 evaluation

	R Square
Service quality	**0.558**

Table 4 demonstrated that service quality (SEVQ), the main endogenous construct, has an R^2 value of 0.558. Thus, the level of the research R2 can be characterised as moderate using the aforementioned rule of thumb.

5.2.2 Predictive Relevance (Q^2) Assessment

The cross-validated redundancy method is utilised in order to evaluate the correlation value of the structural model. This is evaluated with the help of the Stone-predictive Geisser's relevance (Q2), which investigated how accurately the outer model of endogenous latent variables predicted all of the data points for all of the indicators

(Wong, 2016). This approach makes use of the sample reuse technique, which eliminates a portion of the data matrix in order to predict the variables and make predictions based on those estimates while excluding that portion of the data (Hair et al., 2011; Hair et al., 2014). In order for this quality assessment defining feature to have effective predictive relevance, the value of the cross-validated redundancy, abbreviated as Q2, needed to be an integer that was greater than zero. (Chin, 1998). Using a blinded process and the SmartPLS3 software, the final models of the research are analysed in order to determine the cross-validated redundancy (Q2) that is based on the submission that was mentioned (Ringle et al. 2015). The results of the blindfolding procedure are presented in Table 5, which can be found below.

Table 5 - Predictive relevance

Main constructs	SSO	SSE	Q^2 (1-SSE/SSO)
Behavioural intention to use AI	1000.000	1000.000	0.175
Artificial intelligence	2000.000	2000.000	
Service quality	1500.000	1500.000	

The cross-validated redundancy of the structural model displayed in Table 5 shows that the Q^2 values for each endogenous construct are all greater than 0. This demonstrated the research model's strong predictive relevance (Chin, 1998).

5.2.3 Goodness-of-Fit (GoF) Assessment

In comparison to covariance-based statistical tool, PLS-SEM has little a commonly accepted global goodness of fit measure (Vinzi et al., 2010). The effectiveness and structural parameters of the measurements can be used to assess the large-scale and complex model predictive power of accounting (Zainun et al. 2014). In order to measure the overall goodness of fit, Tenenhaus et al. (2004) proposed the "GoF" index. The index is the arithmetic average of the mean communality (AVE) index and the normal of the coefficients of determination (R^2). You can figure it out using the formula below.

$$GoF = \sqrt{\overline{AVE} \; X \; \overline{R^2}}$$

The purpose of the GoF index is to clarify the achievement of the PLS model both at the structural level and the measurement level, with a primary focus on the model's overall performance in terms of its ability to predict (Memon & Rahman, 2013). The AVE (community) term in the equation addresses the accuracy of the measurement items included in the index, whereas the R^2 term in the equation captures the model of the structural component. GoF index values of 0.1, 0.25, and 0.36, respectively, are sorted into the small, medium, and large categories, respectively (Akter, 2011). Calculations are made to determine the global goodness of fit index where GoF of 0.312 was produced by the model. According to Akter's (2011) submission, the research models' GoF is regarded as medium, supporting their high quality.

5.2.4 Hypothesis Testing

PLS-SEM makes an effort to predict how endogenous and exogenous research constructs which are typically expressed in hypotheses will be related causally. To test the hypotheses, the model produces the path coefficients (Hair et al., 2014). Path coefficients are used to judge how well the research's constructs relate to one another in the structural model. Strong positive relationships are seen for path coefficient values close to +1, and vice versa (Hair et al., 2014, Almansoori et al. 2021). Non-parametric bootstrapping was used to calculate the t-value in order to test the hypothesis and assess the path's significance (Rahman et al. 2022). The path coefficients must be significant to ensure the inner model's quality (Wong, 2016). The path co-efficient values obtained for the model are presented in Table 6.

Table 6 - Hypothesis of first component of the model

Hypothesis	Path	Beta Coefficient	T Statistics (|O/STDEV|)	P Values	Relationship
H1	Performance Expect_ -> Service Quality	0.092	4.918	0	Significant
H2	Effort Expectancy_ -> Service Quality	0.285	15.308	0	Significant
H3	Social Influence_ -> Service Quality	0.67	26.773	0	Significant
H4	Facility Condition ->Service Quality	0.007	0.324	0.746	Insignificant

From table 6, it can be concluded that the hypotheses of the first component of the model are as follows;

- **H_1:** Performance expectancy has a significant relationship with the Service quality in the use of AI security technology.
- **H_2:** Effort expectancy has a significant relationship with the Service quality in the use of AI security technology.
- **H_3:** Social influence has a significant relationship with the Service quality in the use of AI security technology.
- **H_4:** Facilitating condition has insignificant relationship with the Service quality in the use of AI security technology.

Table 7 - Hypothesis of second component of the model

Hypothesis	Path	Beta Coefficient	T Statistics (|O/STDEV|)	P Values	Relationship
H5	Service Quality -> Basic AI	0.756	28.377	0.000	Significant
H6	Basic AI -> Behavioural Intention	0.320	4.511	0.000	Significant
H7	Service Quality -> Behavioural Intention	0.575	8.225	0.000	Significant
H8	Service Quality-> Basic AI-> Behavioural Intention	0.287	15.308	0.000	Has mediation effect

From table 7, it can be concluded that the hypotheses of the second component of the model are as follows;

- **H_5:** Service quality has a significant relationship with basic artificial intelligence in the use Al security technology.
- **H_6:** Basic artificial intelligent has a significant relationship with the behavioural intention in the use Al security technology.
- **H_4**: Service quality has a significant relationship with behavioural intention in the use Al security technology.
- **H_8**: Basic artificial intelligent has mediation effect to the relationship between service quality with behavioural intention in the use Al security technology.

Since, the majority of the path coefficients are significant, it can be concluded that the structural research model has the necessary quality.

6. Conclusion

This study sought to look into how well AI technology served security and the desire to use it in the United Arab Emirates. The managerial and operational staff of UAE government agencies that fall under the Ministry of Interior were randomly selected to provide the data. Finding the aspects of service quality that lead to a higher likelihood of using AI security technologies was the first research goal. The use of technology need and intention to use as mediators in the study explored the relationship between service quality performance and the use of Al security technologies. Four hypotheses were developed and PLS model analysis revealed that all the hypothesis are significant. The four hypotheses' findings revealed that all of them were significant. Thus the use of AI security technologies is significantly influenced by service quality. The relationship between service quality and the use of AI security technologies was positively mediated by the fundamental need for AI technology. The study came to the conclusion that better service increases the intention to use AI security technologies because these technologies' support for job performance and user-friendliness raise awareness of their perceived utility, which also encourages others to use them. Additionally, as a result of improved job performance brought about by AI security technologies, users are more dependent on them and more interested in similar future technologies

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