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Measuring Institutions' Adoption of Artificial Intelligence Applications in Online Learning Environments: Integrating the Innovation Diffusion Theory with Technology Adoption Rate

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Abstract: Artificial intelligence applications (AIA) increase innovative interaction, allowing for a more interactive environment in governmental institutions. Artificial intelligence is user-friendly and embraces an effective number of features among the different services it offers. This study aims to investigate users' experiences with AIA for governmental purposes in the Gulf area. The conceptual model comprises the adoption properties (namely trialability, observability, compatibility, and complexity), relative advantage, ease of doing business, and technology export. The novelty of the paper lies in its conceptual model that correlates with both personal characteristics and technology-based features. The results show that the variables of diffusion theory have a positive impact on the two variables of ease of doing business and technology export. The practical implications of the current study are significant. We urge the concerned authorities in the governmental sector to understand the significance of each factor and encourage them to make plans, according to the order of significance of the factors. The managerial implications provide insights into the implementation of AIA in governmental systems to enhance the development of the services they offer and to facilitate their use by all users.

Keywords: artificial intelligence; government sectors; diffusion theory; easy of doing business and technology export

1. Introduction

Artificial intelligence (AI) applications that utilize machine learning are on the rise in different settings, including clinical, agricultural, and educational research, and provide highly promising applications to be used for specific purposes. AI techniques have attracted the attention of technology developers and foreign language researchers in education. However, there is insufficient evidence regarding the actual impacts of AI on students' writing skills, and the conclusions are inconsistent. The use of AI has been largely ignored at the institutional level. The use of AI in educational settings has faced certain barriers that hinder its accurate implementation, fruitful results, and higher levels of achievement [1–4].

The integration of artificial intelligence applications (AIA) into educational systems has many advantages that can help to enhance the effectiveness of learning experiences. Students' participation will be improved if institutions and society appreciate the importance of the integration of these innovational applications into the learning environment. When involving students in an intelligent teaching environment, we should monitor a group of collective factors, including their perceived enjoyment, satisfaction, university support, assumed usefulness, and relative advantage [5,6]. Artificial intelligence has a significant impact on learning achievements, learning domains, and learning methods. The types of software and hardware that are used in the learning environment affect students' readiness to accept new innovational technologies in some countries. Furthermore, learning anxiety, willingness to adopt innovational technologies, and knowledge acquisition are decisive factors that affect students' perceptions, regarding the adoption of innovational technologies.

The diffusion of innovation (DOI) theory comprises the basic elements of innovation, adopters, and communication channels and is extensively implemented as a theoretical basis for the innovation adoption of AI. The core aim of previous studies has been to establish a tendency towards adoption at the micro-level. However, the current study aims to establish a model that incorporates innovation by integrating it into the technology adoption rate while taking institutional perspectives into consideration at the macro level. The technology adoption rate is measured by aligning the diffusion innovation theory variables with the two external variables of ease of doing business (EODB) and technology export (TE) at the intuitional level. The EODB represents the social aspect, while technology exports are related to a society's readiness for innovation. Furthermore, technology exports deal with goods and services that require significant research and resources to invent new technologies according to social needs. Therefore, the diffusion innovation theory with the technology adoption rate represents a strong theoretical background for the process of alignment. Previous studies have tackled the increasing impact of AI in different sectors, including the medical, agricultural, engineering, and other industries [4,7]. Even though AI has been investigated in these sectors, few studies have focused on the significance of AI in the educational sector. In addition, most of these studies take into consideration the improvement of students' skills and their academic achievement [1–3,8]. In contrast with previous studies, this study aims to investigate the adoption of AI at the macro-level. To close the gap in the previous literature, this study intends to investigate the variables that affect the adoption of AI at the institutional level by incorporating the diffusion innovation theory and technology adoption rate.

Artificial Intelligence in Education and Diffusion Innovation Model

Artificial intelligence in education (AIE) is a relatively young field of study. It enhances teachers' knowledge-gap awareness and may provide teachers with a solution to problems in education and enhance its pedagogical aspects. AIE helps teachers to focus on four important factors: personalized instructional materials, innovative structural strategies, technology-assisted assessments, and the communication environment [9].

AIE has ushered in the use of many innovative tools that have proven to be of great significance through the use of the diffusion innovation model. Therefore, the current model is an attempt to embrace various aspects of diffusion models that are applicable to more than one tool. Previous innovation adoption studies have integrated other models to deal with the adoption and acceptance of technologies in education. The strength of the theory lies in the five attributes of innovation influence, which are relative advantage, compatibility, complexity, observability, and trialability. However, the current model focuses on combining the theory of diffusion with other important aspects that can help measure the degree of adoption of new innovations explicitly and add to the value measurement. According to Rogers, the innovation adoption process has two phases: initiation and implementation. The initiation process is already underway for the learning environment. However, the implementation stage still faces many challenges. Therefore, this paper is a step forward towards measuring the crucial importance of the challenges faced by the implementation process [9,10]. This paper attempts to fill a gap in the implementation stage by proposing an integrated conceptual model.

The sections below are organized to tackle the main attributes within the diffusion model in relation to artificial intelligence. A brief summary is given to illustrate how these attributes are related to new innovations. The targeted aim is to support the conceptual proposed model's effectiveness, and the explanation below shows how the diffusion innovation theory is important to easily, practically, and comprehensively tackle the adoption of new innovations related to AI.

The most important attribute is the relative advantage, which is the most powerful factor in innovation adoption. It can easily measure the adoption of new technology. If AI technology is viewed as useful and fruitful during the implementation process, then users are more likely to use it. Similarly, compatibility helps us to measure how innovation will fit into a new structure, which involves users' needs, the value of the existing technology, and the users' beliefs. It has been proposed that the higher the compatibility, the better the adoption. However, surprisingly, when the compatibility is too high, the new technology might not be perceived as innovative enough to adopt [10,11].

On the other hand, complexity refers to perceptions about innovation, in terms of the difficulty of comprehending or using it. Whenever the innovation includes new technologies and innovative features, it will be perceived as highly advanced and advantageous if the technology has a lower level of complexity and can be described as simple. Observability refers to the degree of ease with which the innovation can be shared and visible results can be obtained after use. This attribute focuses on the observed results that can enhance the adoption of innovation. High observability will lead to the faster adoption of the new technology due to the transparent obtained results. In this respect, observability can be discussed from two different perspectives. The first is the visibility of the results and the second is the demonstrability of the results, the latter of which focuses on measuring tangible performance. Finally, trialability allows organizations to examine the innovation partially before its full adoption. This factor is well aligned with modern innovations and gives its creators the end users' perceptions, regarding the adoption or rejection of the new innovation [12,13].

2. A Comprehensive Review for AI in Education

AI techniques can help in the development of significant qualities that are related to educational settings, such as self-reflection, answering complex questions, resolving problems, and choice-making skills [14–16]. Prior studies have examined the role of and research interest in artificial intelligence in the educational sector. The main focus of these studies has been the contribution of appropriate models, research methodologies, and language skills, especially with regard to reading, writing, and vocabulary acquisition. Learning anxiety, willingness to communicate, knowledge acquisition, and classroom interaction are the core factors that may affect the adoption of AI. The personal characteristics of participants may be considered an added value for the adoption of AI, which include critical thinking ability and complex problem-solving skills. Studies have shown that the effective use of AI in educational settings leads to a change in the entire government's attitude towards the use of these applications. The effectiveness of the usage and implementation may affect teachers' and students' perceptions regarding their learning styles and strategies, which may enrich or affect how they learn, what they learn, and when they learn. The direct impact of AI affects decision-makers at institutions of higher education [1–3,8].

Teachers' perceptions have been investigated by previous studies that focused on their ability to adapt to and accept AI. These studies examine the experiences of teachers at schools who have participated in the implementation of AI applications. The eagerness of members of the sample group to prepare the user environment and create a structural organization was one of the key factors that enhanced the adoption of AI at the school level. The features of AI technologies may accelerate their adoption. Studies have found that their perceived ease of use and perceived usefulness may affect the adoption positively and significantly. On the other hand, teachers' AI anxiety may affect its adoption negatively, as it may discourage teachers from using these technologies due to their fears and worries [6,8]. In one study [2], a model of willingness was created to measure participants' attitudes towards the use of AI technologies in China. The model focused on the importance of crucial factors, such as perceived risk and perceived entertainment variables. The results showed that users are more likely to use the AI technologies if there is sufficient support, i.e., sustainable development and educational belief in the significant role of this innovation.

3. Recent Studies of Artificial Intelligence in Education (AIE)

The literature review is full of examples that support the importance of AI in the educational environment as shown in Table 1. This section focuses on the main crucial studies on AIE during the years 2022–2023. Studies have shown variations in terms of their data collection, research methodology, research purposes, obtained results, and field of interest. One study [9] showed that there is a need to discuss the way artificial intelligence tools are potentially integrated into global education, as it can be affected by the place where it is implemented, the type of the educational innovation, and the degree of deviation from the traditional norms. Another study focused on the importance of the academic and administrative applications of artificial intelligence. It paid more attention to the role of teachers and their responsibility in the educational environment [16]. Similarly, another study [17] focused on the role of teachers in AIE, emphasizing the fact that AI can effectively reduce teachers' workload and create a revolution in the assessment methodology, leading to rich developments in the intelligent tutoring system. Despite the fact that these previous studies have come to similar conclusions, one study [18] has demonstrated that young learners have to be treated differently. The researchers stated that AIE has to be dealt with differently when it comes to young learners, due to their need for huge input to facilitate the process of education. However, few studies have focused on the relation between artificial intelligence and machine learning. It is assumed that students' performance can be improved whenever AI tools require less effort, support both poor and average learners, and measure the level of improvement clearly.

Table 1. Recent AIE studies field of interest.

Authors Details	Purpose of the Study	The Obtained Results	Field of Interest
[9]	The study aims at investigating the possible way of AI integration in global education.	The AI is affected by factors, such as the place of adoption, the type of AI tool and the users' perception towards it.	The AI and Global Education
[16]	The purpose of the study is to explore importance of the academic and administrative applications of Artificial Intelligence.	AIE has a crucial role, since it minimizes the burden on the teachers' shoulder and facilitates the process of teaching.	Academic and Administration role in AIE
[17]	The study aims at investigating how the intelligent tutoring system may reduce teaching load, leading to development in assessment methods.	AIE may affect the teachers' load, students' engagement, and assessment methods positively.	Intelligent Tutoring System in Education

Table 1. *Cont.*

Authors Details	Purpose of the Study	The Obtained Results	Field of Interest
[21]	The study aims at discovering how machine learning-based frameworks can affect students.	AIE can affect positively students' performance. The obtained results is arrived at after adopting a model that incorporates three machine learning algorithms, which are support vector machine, random forest and regression analysis.	Artificial Intelligence and Machine Learning
[18]	The study focuses on the challenges of implementing AI tools, in terms of why, what, and how.	AIE has to be dealt with differently when it comes to young learners, due to their special need of huge input to facilitate the process of education.	Artificial Intelligence and Children Education
[19]	The study aims at investigating possible ways of integrating AI into language education.	AI affects different aspects in language education, such as vocabulary learning, writing and speaking skills, and grammar. AI facilitate the process of learning in wring, reading, and vocabulary learning and pronunciation development.	Artificial Intelligence and Language Learning
[20]	The study investigates the gap that is related to the lack of reflection on how professor can integrate AI in a learning environment to improve the pedagogy framework.	The integration of AI needs a reconsideration of how the pedagogical framework is integrated in the educational setting. The pedagogy framework can enhance the professional level of education at higher education	Artificial Intelligence and Pedagogy Framework

Some other studies have focused on different fields of interest by investigating the effect of AI on language learning. The use of AI to create an intelligent tutoring system may positively affect the learning of different language skills. It can also enhance the learning of new vocabulary words and accurate pronunciation [19]. In a similar vein, another study focused on the role of AI in developing the pedagogy framework in higher education, illustrating that the pedagogy framework is a key concept in AIE because it helps learners to make use of various cognitive skills at the university level [20].

4. Theoretical Framework and Hypotheses Development

The DOI theory and technology adoption rate are key elements that play a decisive role in the adoption of new technologies both at the institutional and social levels. The application of the DOI implies that the focus is going to be on the relative advantage of a technology when there is a chance to adopt it [22]. Accordingly, the previous studies lack an understanding of how institutional forces impact organizational artificial intelligence adoption [5]. With this in mind, little is known about the impact of institutional impacts and stakeholders on the adoption of artificial intelligence applications in the educational sector. No studies have yet attempted to explore the interrelatedness of the innovation diffusion theory's factors and other macro-level factors that crucially affect the adoption of innovational technologies. This research consequently tests hypotheses that investigate students' perceptions, institutions' readiness, and society's acceptance when it comes to adopting artificial intelligence applications in education (see Figure 1 below).

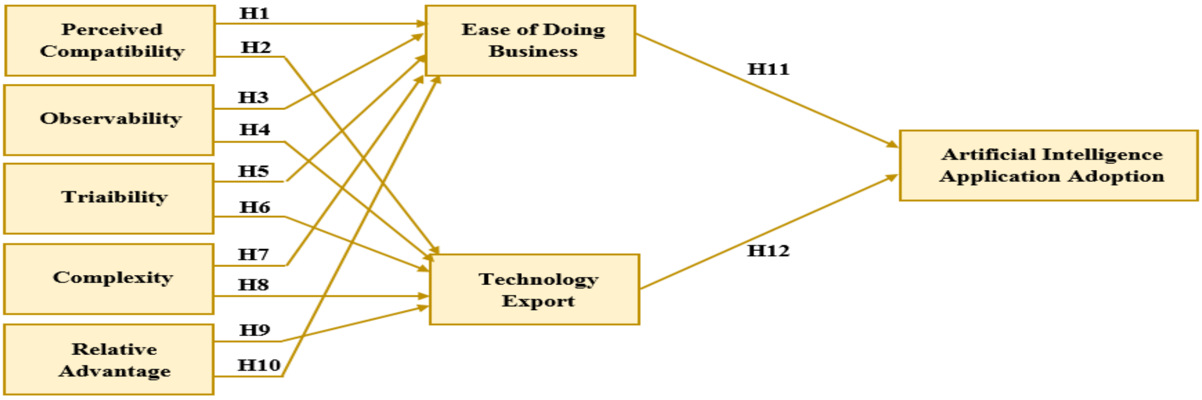

Figure 1. Research Model.

4.1. The Diffusion of Innovation Theory (DOI Theory)

The diffusion of innovation theory investigates methods of infusing novel technologies across a social system. It involves the variables relative advantage, compatibility, observability, trialability, and perceived complexity, which can all effectively impact organizational technology adoption [23]. In contrast with TAM and UTAUT, DOI focuses on the context within which the decision of adoption is taken, making it an appropriate tool for analyzing the complexities related to the organizational adoption of innovative technologies. Despite the fact that the theory involves a group of contextual factors, it still highlights the importance of technology-specific aspects, such as relative advantage [24–26]. One of the limitations of this theory is that it does not focus on additional dimensions such as environmental or organizational dimensions. Therefore, the current study incorporates the significant factor of the technology adoption rate to establish a unique framework that can account for these macro-level perspectives.

The most significant variable in the diffusion of innovation theory is the perceived compatibility (PC), which is defined as the degree to which society trusts the AI technologies and applications under conditions where the technology is inconsistent with the existing values, experience, or potential needs of the users. The more the technology is perceived as compatible with the requirements and experiences of users, the more the users are willing to adopt it. Accordingly, this study limits the definition of the perceived compatibility to the degree that institutions and users believe that AI can increase information systems' potential and enhance their performance [27]. Trialability (TR), on the other hand, is the extent to which society trusts innovations. Trialability refers to the degree to which learners are encouraged to use AI technologies and applications in the future [28–30]. Complexity (CO) is the end user's perceived level of effort required to understand inventions and their simplicity of use. Complexity refers to the degree of difficulty that learners consider using the AI system to entail, which may affect their performance negatively. Observability (OB) is the degree to which the AI is seen as visible to the users and others. Visibility implies that AI can assist with a peer discussion of a new idea as learners seek discussion and negotiation over the innovation. Finally, relative advantage (RA) is the extent to which users believe that the innovation is better than the traditional method. Therefore, in this research, the relative advantage is defined as the degree to which learners believe that AI is a technology that is better than traditional techniques that can positively affect their future performance. The following hypotheses can be formulated regarding the adoption of AI in the current study:

Hypothesis (H1): *Perceived compatibility (PC) positively affects ease of doing business (EODB).*

Hypothesis (H2): *Observability (OB) positively affects ease of doing business (EODB).*

Hypothesis (H3): *Trialability (TR) positively affects ease of doing business (EODB).*

Hypothesis (H4): *Complexity (CO) negatively affects ease of doing business (EODB).*

Hypothesis (H5): *Relative advantage (RA) positively affects ease of doing business (EODB).*

Hypothesis (H6): *Perceived compatibility (PC) positively affects technology export (TE).*

Hypothesis (H7): *Observability (OB) positively affects technology export (TE).*

Hypothesis (H8): *Trialability (TR) positively affects technology export (TE).*

Hypothesis (H9): *Complexity (CO) negatively affects technology export (TE).*

Hypothesis (H10): *Relative advantage (RA) positively affects technology export (TE).*

4.2. Ease of Doing Business (EODB)

EODB is a significant indicator that shows the environments that are most ready to embrace new technology. EODB is a crucial factor that affects people's willingness to accept innovations. It is a unique measurement that illustrates how macro-level institutions handle crucial business issues. A company's readiness to facilitate the use of technology paves the way for its flourishing. When people think that it is easy to do business, this implies that they are more likely to adopt new technologies [31,32]. Based on the previous assumption, it is hypothesized that:

Hypothesis (11): *The ease of doing business has a positive impact on the adoption of AI.*

4.3. Technology Export (TE)

Technology export deals with goods and services that require significant research and resources to develop according to social needs. It may include different elements starting from technological support and innovation to instrumentation and electrical equipment [33]. Recently, societies have witnessed a shift towards types of technologies that are categorized as high-technology exports, where new technologies are invented in advanced economies but are diffused and exported to less developed countries. Thus, receptive countries are countries that are less familiar with a technology and its technological distribution [33,34]. Therefore, the technology export variable is an external variable that has an influential role in measuring the impact of technology adoption. Thus, it is hypothesized that:

Hypothesis (12): *The technology export of a country has a positive impact on the adoption of AI.*

5. Methodology

5.1. Data Collection

Data were collected using online surveys at Al Buraimi University College in Oman between 10 February and 20 May 2022. The research team randomly distributed 300 questionnaires. The respondents answered 273 questionnaires, which represented 91% of the surveys. A total of 27 questionnaires were rejected due to missing values. As a result, the number of usable questionnaires was 273. These questionnaires were accepted on the basis of Krejcie and Morgan's [35] estimates of sample size (the expected number of respondents for a population of 300). There is a great difference between the sample size (273) and the minor requirements. With this in mind, the sample size has been analyzed and evaluated using structural equation modelling [35], which was used to confirm the hypotheses. It is important to mention that the existing theories (based on the technology adoption rate) were the foundation of our hypotheses. Regarding the evaluation of the measurement model, structural equation modeling (SEM) (SmartPLS Version 3.2.7) was used by our research group. Advanced treatment was conducted with the help of the final path model.

5.2. Students' Personal Information/Demographic Data

Table 2 illustrates the distribution of the demographic/personal data that were collected for the sake of analysis. The percentage of male students was 47%, whereas the percentage of female students was 53%. Furthermore, 61% of respondents were within the age range 18–29 years, and the rest were over 29. Most of the respondents were university students who had gained expertise and good qualifications. Most of the respondents had different university degrees. The percentages of students who had a bachelor's degree, master's degree, and doctoral degree were 69%, 23%, and 8%, respectively. In a past study [36], they brought up the idea that there are instances where the respondents show willingness to volunteer. This can be considered the "purposive sampling approach". Therefore, the sampling tool includes all respondents who are university students with different ages and various majors. IBM SPSS Statistics ver. 23 was used to measure the demographic data. Table 2 represents a deeper view of the respondents' demographic data.

Table 2. Demographic data of the respondents.

	Factor	Frequency	Percentage
Gender	Female	144	53%
	Male	129	47%
Age	Between 18 to 29	167	61%
	Between 30 to 39	72	26%
	Between 40 to 49	26	10%
	Between 50 to 59	8	3%
Education qualification	Bachelor	189	69%
	Master	62	23%
	Doctorate	22	8%

5.3. Study Instrument

A survey instrument was used in the current study to validate the hypothesis. A precise measurement tool, which is needed to measure the questionnaire's eight constructs, was chosen efficiently. A total of 23 items were added to the survey. The source of these constructs is illustrated in Table 3, which is presented to make the research constructs more practical and to support the current model with evidence from the existing literature. Finally, the researchers made amendments to the questions of prior studies.

Table 3. Measurement Items.

Constructs	Items	Definition	Instrument	Sources
Perceived Compatibility	PC1	Perceived compatibility (PC) which is defined as the degree to which society trust the IA technologies and applications under the condition that the technology is in consistent with the existing values, past experience, and the potential needs of the users.	AI technologies are compatible with the current educational system.	[27]
	PC2		AI technologies are compatible with the learning styles and teaching strategies.	
	PC3		AI technology is not consistent with the current educational platform.	

Table 3. *Cont.*

Constructs	Items	Definition	Instrument	Sources
Trialability	TRI1	Trialability refers to the degree to which learners view acceptability of AI technologies and applications as encouraging and stimulating future uses. [28,37]	AI technology provides chances for future usages.	[28,37]
	TRI2		AI technology helps in assessing future educational tasks.	
	TRI3		AI is innovative because it provides chances to have rich content in educational settings.	
Complexity	CO1	Complexity (CO) refers to the degree to which learners consider the difficulties behind using the AI system, which may affect their performance negatively.	AI technology is more difficult than usual technologies in daily usage.	[28,37]
	CO2		AI technology is harder to follow, as compared to the old technology.	
	CO3		AI technology has complicated features that cannot be implemented in educational settings.	
Observability	OB1	Observability (OB) is the degree to which the AI is seen as visible to the users and others.	AI is viewed as being informative and successful by other institutions	[28,37]
	OB2		AI is considered as a useful tool in developing teaching–learning environments by academic staff.	
	OB3		AI technology is categorized under innovational technology by neighbor countries.	
Relative advantage	RA1	Relative advantage (RA) is the extent to which users believe that innovation is better than the traditional one.	AI technology provides more educational features than old ones.	[28,37]
	RA2		AI technology helps me to save time and effort, as compared with old system.	
	RA3		AI technology is not consistent with the current educational platforms.	
Ease of Doing Business	EODB1	EODB is a crucial factor that assist the level of people readiness to accept new innovation [31].	AI technology is widely accepted at the institutional level	[31]
	EODB2		AI technology is known by many adopters in our society.	
	EODB3		AI technology is preferred by academic staff and students.	
Technology Export	TE1	Technology exports deals with goods and services requiring significant research and resources to invent new technologies, according to the social needs. It may include different elements starting from technological support and innovation to instrumentation and electrical equipment [33].	IA technology satisfies the societal needs; it was invented by other countries.	[33]
	TE2		AI technology innovation features are highly demanded at the institutional level.	
	TE3		IA technology does not satisfy the academic staff needs.	
Technology Acceptance Rate	TAR1	Technology acceptance rate is instantiated as a macro level indicator of the adoption of technology in a country.	Institutions are ready to adopt AI technology for educational purposes.	[38]
	TAR2		Institutions are willing to upgrade their education platforms and ready to include AI as part of it.	

5.4. Pilot Study of the Questionnaire

To measure the reliability of the questionnaire item, a pilot study was conducted. The selection of the data was random and involved the selection of 30 students from the population for this pilot study, which was 10% of the total sample size. To better analyze the pilot study outcomes, we utilized Cronbach's alpha test for internal reliability via IBM SPSS Statistics ver. 23. This procedure assists the process of yielding acceptable conclusions for the measurement items. According to the stated trend of studies on social sciences, a 0.70 reliability coefficient is considered acceptable [39]. Table 4 presents the Cronbach's alpha values in terms of the five measurement scales.

Table 4. Cronbach's alpha values for the pilot study (Cronbach's alpha $\geq$ 0.70).

Construct	Cronbach's Alpha
CO	0.715
EODB	0.700
OB	0.791
PC	0.781
RA	0.848
TAR	0.881
TE	0.863
TRI	0.812

5.5. Survey Structure

The questionnaire survey had three different sections and was distributed among a group of students [40].

- The first section involved the respondents' personal data.
- The second section contained two items related to the technology acceptance rate.
- The third section contained 21 items related to complexity, ease of doing business, observability, perceived compatibility, relative advantage, technology export, and trialability.

To enable us to measure the 23 items efficiently, a five-point Likert scale was adopted with the responses strongly disagree (1), disagree (2), neutral (3), agree (4), and strongly agree (5).

6. Findings and Discussion

6.1. Data Analysis

The data analysis of the current study involved partial least squares-structural equation modeling (PLS-SEM) through SmartPLS V 3.2.7 [41,42]. The data were collected using a two-step assessment approach. This approach includes a measurement model and a structural model [43]. PLS-SEM was chosen in the current study for a number of reasons that have been enumerated throughout the paper. The first reason that has to be considered is the analysis of the conceptual theory that is proposed in the current study, which lends itself well to PLS-SEM [44,45]. The second reason is that the PLS-SEM effectively handles exploratory research on conceptual models [46]. The third reason is that implementing the PLS-SEM allows us to analyze the entire model as one unit rather than having to subdivide it [47]. The final reason is that we can gain a concurrent analysis of the structural and measurement models, depending on the PLS-SEM. The importance of PLS-SEM lies in the accuracy of the measurements that it can generate [48].

6.2. Convergent Validity

For the purpose of assessing the measurement model, [43] suggested the constructs reliability (which includes Cronbach's alpha (CA), Dijkstra–Henseler rho (PA), and composite reliability (CR)) and validity (which includes discriminant and convergent validity). To determine the construct reliability, Cronbach's alpha (CA) was found to be within the range of 0.821–0.895, according to Table 5. The threshold value (0.7) is lower than these figures [49]. According to Table 5, the composite reliability (CR) values range from 0.835 to 0.923, which exceed the threshold value [50]. Rather than these two values, we believe that researchers should use the Dijkstra–Henseler rho (pA) reliability coefficient to evaluate and report constructs' reliabilities [51]. As with CA and CR, the reliability coefficient ρA should be at least 0.70 (for exploratory research) or 0.80–0.90 (for advanced research stages) [49,52,53]. Table 4 also shows that 0.70 is the minimum reliability coefficient ρA of all measurement constructs. These results confirm the construct's reliability, and each construct was ultimately considered to be free of errors.

Table 5. Convergent validity results which assures acceptable values (Factor loading, Cronbach's alpha, composite reliability, Dijkstra–Henseler's rho ≥ 0.70 & AVE > 0.5).

Constructs	Items	Factor Loading	Cronbach's Alpha	CR	PA	AVE
Complexity	CO1	0.732	0.829	0.856	0.867	0.573
	CO2	0.850				
	CO3	0.775				
Ease of Doing Business	EODB1	0.776	0.846	0.861	0.836	0.640
	EODB2	0.855				
	EODB3	0.895				
Observability	OB1	0.861	0.821	0.835	0.858	0.724
	OB2	0.957				
	OB3	0.898				
Perceived Compatibility	PC1	0.891	0.895	0.923	0.903	0.643
	PC2	0.844				
	PC3	0.884				
Relative advantage	RA1	0.879	0.833	0.831	0.875	0.629
	RA2	0.932				
	RA3	0.916				
Technology Acceptance Rate	TAR1	0.895	0.884	0.887	0.813	0.735
	TAR2	0.799				
Technology Export	TE1	0.843	0.842	0.840	0.876	0.772
	TE2	0.859				
	TE3	0.864				
Trialability	TRI1	0.742	0.884	0.874	0.887	0.562
	TRI2	0.849				
	TRI3	0.850				

As far as the measurement of convergent validity is concerned, it is extremely important to test the mean variance extracted (AVE) and factor loading [43]. Table 5 shows that each factor loading value exceeded the threshold value of 0.7, apart from the previously mentioned ones. Furthermore, Table 5 illustrates that the AVE values ranged from 0.562 to 0.772, which exceed the 0.5 threshold value. Consequently, due to the previously mentioned explanation, it is likely that our study has convergent validity.

6.3. Discriminant Validity

This study intended to measure the discriminant validity. Hence, it was suggested that we revisit two criteria: the Heterotrait–Monotrait ratio (HTMT) and the Fornell–Larcker criterion [43]. The findings, which are given in Table 6, illustrate that the Fornell–Larcker condition confirms the requirements because each AVE and its square root exceeds its correlation with other constructs [54].

Table 6. Fornell–Larcker Scale.

	CO	EODB	OB	PC	RA	TAR	TE	TRI
CO	**0.867**							
EODB	0.525	**0.882**						
OB	0.472	0.110	**0.888**					
PC	0.667	0.212	0.648	**0.872**				
RA	0.208	0.411	0.464	0.551	**0.812**			
TAR	0.660	0.044	0.364	0.438	0.104	**0.807**		
TE	0.467	0.150	0.250	0.394	0.529	0.690	**0.898**	
TRI	0.351	0.543	0.555	0.147	0.214	0.663	0.402	**0.847**

Table 7 shows the HTMT ratio findings, which shows that the value of each construct is lower than the 0.85 threshold value [55]. With the help of these findings, we calculated the discriminant validity. According to the analysis results, there was not a single issue related to the measurement model when it came to its reliability or validity. Because of this, the collected data can be further used to evaluate the structural model.

Table 7. Heterotrait–Monotrait Ratio (HTMT).

	CO	EODB	OB	PC	RA	TAR	TE	TRI
CO								
EODB	0.225							
OB	0.512	0.665						
PC	0.537	0.533	0.215					
RA	0.259	0.538	0.240	0.497				
TAR	0.305	0.438	0.371	0.325	0.212			
TE	0.424	0.412	0.504	0.577	0.700	0.616		
TRI	0.638	0.003	0.205	0.711	0.250	0.194	0.339	

6.4. Hypotheses Testing Using PLS-SEM

The structural equation model was developed using Smart PLS and uses the maximum likelihood estimation to identify the interdependence of several theoretical constructs of a structural model [56–62]. Following this procedure, the suggested hypotheses were analyzed. They are illustrated in Tables 2 and 8, showing that the model had a moderate predictive power [63]; that is, the percentage of the variance within the technology acceptance rate was nearly 63% as shown in Table 8.

Table 8. R^2 of the endogenous latent variables.

Construct	R^2	Results
EODB	0.541	Moderate
TE	0.554	Moderate
TAR	0.628	Moderate

In Table 9 and Figure 2, the beta (β) values, t-values, and *p*-values of all developed hypotheses are described on the basis of the produced findings with the help of the PLS-SEM technique. There is no doubt that all hypotheses are supported; when taking into consideration the data analysis hypotheses, the empirical data show support for H1, H2, H3, H4, H5, H6, H7, H8, H9, H10, H11, and H12.

Table 9. Hypotheses testing of the research model (significant at ** *p* < = 0.01, * *p* < 0.05).

H	Relationship	Path	*t*-Value	*p*-Value	Direction	Decision
H1	PC -> EODB	0.521	7.699	0.000	Positive	Supported **
H2	PC -> TE	0.519	5.265	0.000	Positive	Supported **
H3	OB -> EODB	0.615	4.826	0.000	Positive	Supported **
H4	OB -> TE	0.796	5.719	0.000	Positive	Supported **
H5	TRI -> EODB	0.432	3.307	0.001	Positive	Supported **
H6	TRI -> TE	0.517	4.476	0.000	Positive	Supported **
H7	CO -> EODB	0.221	0.102	0.029	Positive	Supported *
H8	CO -> TE	0.384	2.307	0.021	Positive	Supported *
H9	RA -> EODB	0.549	4.905	0.000	Positive	Supported **
H10	RA -> TE	0.815	24.627	0.000	Positive	Supported **
H11	EODB -> TAR	0.915	24.627	0.000	Positive	Supported **
H12	TE -> TAR	0.817	24.627	0.000	Positive	Supported **

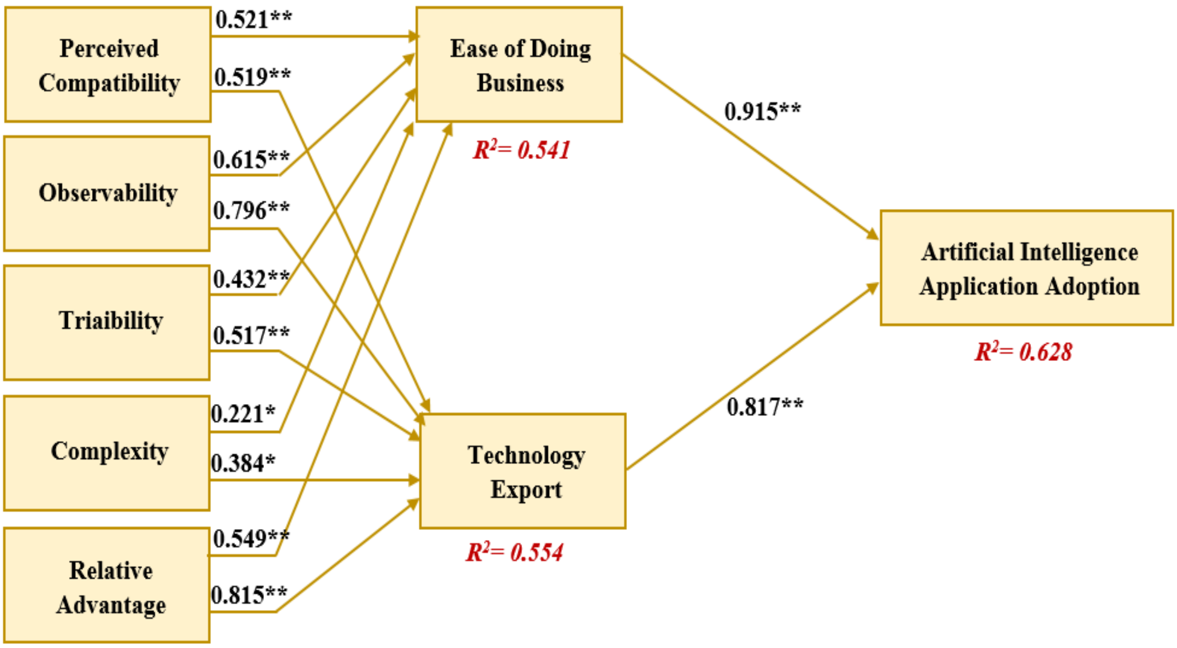

Figure 2. Path coefficient of the model (significant at ** *p* < = 0.01, * *p* < 0.05).

The perceived compatibility (PC), observability (OB), trialability (TRI), complexity (CO), and relative advantage (RA) have significant effects on the ease of doing business (EODB) (β = 0.521, $p < 0.001$; β = 0.615, $p < 0.001$; β = 0.432, $p < 0.001$; β = 0.221, $p < 0.05$; and β = 0.549, $p < 0.001$, respectively). Hence, H1, H3, H5, H7, and H9 are supported, respectively. The results also showed that technology export (TE) significantly influenced perceived compatibility (PC) (β = 0.519, $p < 0.001$), observability (OB) (β = 0.796, $p < 0.001$), trialability (TRI) (β = 0.517, $p < 0.001$), complexity (CO) (β = 0.384, $p < 0.05$), and relative advantage (RA) (β = 0.815, $p < 0.001$), supporting hypotheses H2, H4, H6, H8, and H10, respectively. The ease of doing business (EODB) and technology export (TE) have significant effects on the technology acceptance rate (TAR) (β = 0.915, $p < 0.001$, and β = 0.817, $p < 0.001$, respectively); hence, H11 and H12 are supported.

7. Discussion of Results

The overall objective of this research was to evaluate the adoption of artificial intelligence applications (AIA) at the governmental level. In our attempt to fulfil this objective, two main variables were specified, which guided this research project. In particular, the ease of doing business and technology export were the two crucial factors that identified and influenced the adoption of artificial intelligence applications, in relation to other independent factors. The diffusion theory that comprises several independent variables determines the extent to which these variables can affect the adoption of AIA. The findings of the study show that the ease of doing business (EODB) and technology export (TE) have a direct impact on adoption. The current findings are inconsistent with previous studies that show that EODB has a high impact on the adoption of technology. As a result of EODB, one can see what type of environment is most primed to enhance new technologies. People's readiness to accept innovation is greatly enhanced by EODB. An institution's ability to handle crucial business issues can be demonstrated by this unique measurement. Business flourishes when companies are ready to utilize technology. The belief that it is easy to do business implies that people will adopt new technologies more efficiently. Similarly, the existing literature has dwelled on the effectiveness of technology export, stating that technological exports include goods and services that require significant research and resources to develop. In addition to technical support and innovation, electrical equipment and instrumentation can be included in the development of technology. All these variables are effective in the adoption of AIA, in relation to technology export.

The other five factors that may correlate with the two previously mentioned variables are relative advantage, complexity, compatibility, trialability, and observability. Statistical analyses have identified a number of key findings that contributed to the study's objective. Based on the statistical analysis, the findings have shown that there is a significant relationship between the various variables of the conceptual model.

First, there is a remarkable relation between relative advantage, complexity, compatibility, trialability, and observability and the ease of doing business. This positive correlation signifies that governments can work more efficiently whenever technology meets their needs easily without any further complications. The lack of complexity in carrying out actions implies that the adoption level will be higher and more effective. According to [64], technology adoption is associated with relative advantage awareness, availability, user-friendliness, service quality, network reliability advantages, and convenience. In [65], perceived value is closely related to an innovation's relative advantage. It is more important for users to believe that innovations will benefit them rather than for them to have an objective advantage over precedents. According to the diffusion of innovation theory, the better an innovation's perceived relative advantage, the faster it will spread.

Based on these findings, compatibility and AIA are significantly related. It has been found that the major variable affecting technology is compatibility [66,67]. A study by [68] shows that incompatible innovations are less likely to be adopted than compatible ones, suggesting that they need a forcing function to overcome challenges and take advantage of opportunities. Accordingly, compatibility as an independent variable can aid in determining the level of adoption at the governmental level, providing an early indicator of the high significance of this factor [69–74].

7.1. Theoretical and Practical Implications

From the theoretical point of view, the current study contributes to the literature by signifying that diffusion theory and its variables have positive consequences on the ease of doing business and technology export in the context of AIA. The implications of this finding encourage users in government sections to use AI and develop a positive attitude towards it and willingness to continue using it. The current study adds to the existing literature by reinforcing the conclusions of previous studies regarding the efficiency of diffusion theory. The last theoretical implication is that government institutions have a high trust level when it comes to AI and have technology readiness regarding this issue.

The practical implications are related to the success that can be achieved in developing services at the governmental level. The ease of doing business and technology export can significantly affect users' willingness to use AIA and trust in AIA. The fact that compatibility was found to have a positive correlation with the intention to adopt AI suggests that the adoption rate for AI can be increased if the developers of these applications can implement more compatible features. Hence, application developers and programmers should consider adding more tools and ways to engage with users, avoiding features that deviate from the traditional tools used at government institutions. Similarly, the positive association between observability, relative advantage, and trainability leads to a higher level of adoption intention, altering the traditional attitudes towards government institutions and leading to a more developed and attainable system. The system can be developed by providing detailed information about the procedure of implementation through official websites and advertisements. Thus, these tools can be used as training procedures to pave the way for a more innovative system in the future.

7.2. Managerial Implications

Based on the result of the study, the managerial implications can serve the government sector, allowing for more creative implementation of AIA. AIA are considered innovative technologies that can facilitate the life of humans and enhance their personal development. Our findings provide deeper insights into the fact that development and innovation are necessary at the governmental level. People who are in charge should encourage their government institutions to adopt AIA. Developers and managers can benefit from the current findings when facing persistent challenges due to the obstacles and complexity that may arise from using AI, which can negatively affect the physical comfort and safety of the adoption. Accordingly, application developers should reshape their understanding of the recommended features that help to spread knowledge about the importance of AI at the government level.

7.3. Limitations of the Study and Future Studies

The current study has many limitations. The first limitation is that the research model is limited to a group of factors that serve as tools to investigate the effect of AIA. Future studies may add other variables that serve users' goals and objectives, focusing on the investigation of factors influencing the adoption intention of AI. The second limitation is that the current study focuses on governmental sectors without specifying a particular one. Accordingly, we implore future research to address this concern by considering the educational, health, and banking sectors and measuring the influence of AI in universities, hospitals, colleges, banks, etc. Furthermore, since our research evidence came from a single country, it is not possible to claim that our findings are generalizable. To better understand this timely and necessary topic, further studies in other settings are required to validate our findings. Finally, this study has provided insights on the relevance of DOI theory to AIA in the governmental sector in developing countries. Future studies may adopt other theories to reach results that can build upon ours.

8. Conclusions

The adoption of AIA will provide future insights into the role of technology in different governmental sectors, providing substantial benefits via improved efficiency. Our study concludes that DOI theory has an efficient measure that is related to its relative advantage, complexity, compatibility, trialability, and observability. These factors all influence AIA adoption in governmental institutions. The study concludes that compatibility has a significant influence on the ease of doing business and technology export. The reason behind this high impact is the fact that adopters are likely to see innovation as being compatible with their life and lifestyle. If AIA meets the needs of the government's plans, the users will benefit to a great extent from the innovation of the technology. Thus, users can seamlessly adapt and replace an existing product or idea for the better. In addition, this study concludes that trialability has a remarkable impact on AIA adoption because it is critical to facilitating the adoption. This stems from the fact that users would like to see what AIA can do and give it a test run before committing to it. Similarly, our study concludes that observability has a positive impact on AIA adoption because users can observe the benefits of adopting and using it. Complexity slows down the adoption process due to the difficulty that users may experience. The more complex an AIA is, the more difficult it is for adopters to incorporate it into their lives. The government is more willing to adopt AIA, which provides more innovative features that will supply government sections with solutions and possible future developments. Finally, the study recommends the use of AI in various governmental institutions in order to achieve better future development.

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