International Journal of Data and Network Science 7 (2023). 457–466

Contents lists available at GrowingScience

International Journal of Data and Network Science

homepage: www.GrowingScience.com/ijds

The adoption of artificial intelligence applications in education

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CHRONICLE

Article history:
Received: June 14, 2022
Received in revised format: July 28, 2022
Accepted: August 31, 2022
Available online: August 31 2022

Keywords:
Artificial intelligence
Educational sectors
Diffusion theory
Easy of doing business
Technology export

ABSTRACT

Artificial intelligence is user-friendly and possesses useful characteristics to share across the various services that are provided. By enhancing innovative contact, artificial intelligence applications (AIA) enable a more involved environment in governmental institutions. The goal of this study is to discover how users in the UAE feel about using AIA for educational reasons. Data collected from a survey of 387 university students were used to validate the model and hypotheses. The adoption features, such as perceived compatibility, trialability, relative advantage, ease of doing business, and technology export, are included in the conceptual model. The current study's practical implications are crucial in that they push the relevant educational authorities to comprehend the significance of each component and enable them to make plans and efforts in accordance with the order of the factors' relative importance. The managerial implications give educational sectors insight on how to apply AIA in their system to improve the growth of the provided service and to make the process easier for all users. The conceptual model of the paper, which links both traits of the individual and those of the technology, is what makes it new. The findings indicate that the diffusion theory variables outperform the other two variables of ease of doing business and technology export.

1. Introduction

Technology researchers and experts in the teaching of foreign languages have been interested in AI techniques. Applications of artificial intelligence (AI) that use machine learning are becoming more prevalent in a variety of contexts, including clinical, agricultural, and educational research. These applications hold great promise for usage in a variety of contexts. There are some obstacles that prevent accurate implementations, beneficial outcomes, and greater levels of accomplishment when using AI in educational contexts (Chatterjee & Bhattacharjee, 2020; Liang et al., 2021; Liu et al., 2021; Varghese, 2020). The effect of AI on students' writing skills has a lack of data and conflicting findings. At the institutional level however, the use of AI has been somewhat overlooked.

The success of learning, the areas of learning, and the methods of learning are all significantly impacted by artificial intelligence. The kid's individual qualities are equally crucial. The effectiveness in learning experiences is one of the benefits of integrating artificial intelligence applications in educational systems. The perceived enjoyment, satisfaction, and university support, along with its expected usefulness and relative advantage, should all be present for students to participate in an intelligent teaching environment (Ukobitz & Faullant, 2022). If institutions and society endorse the significance of integrating these advanced applications into the learning environment, then student engagement will increase. In some countries, the kind

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ISSN 2561-8156 (Online) - ISSN 2561-8148 (Print)

doi: 10.5267/j.ijdns.2022.8.013

of hardware and technology software utilized in the learning environment has an impact on student's willingness to adopt new innovative technologies. Future adoption of innovative artificial intelligence applications may be facilitated by student's strong problem-solving and critical thinking skills (Liang et al., 2021; Zheng et al., 2021). Additional aspects that have a significant impact on student's perceptions of embracing innovative technologies include less learning anxiety, a willingness to use those technologies, and knowledge achievements.

To create a conception of adoption at the micro-level was the main objective of Prior research. In contrast to earlier studies, this tries to look into the macro-level adoption of AI. The growing impact of AI on a variety of industries, including medicine, agriculture, engineering, and others, has been the subject of earlier research (Varghese, 2020). The current study keeps institutional views in account at the micro-level, and tries to create a model taking innovation into account by including it into the Technology Adoption Rate. The fundamental elements of innovation, adopters, and communication routes are covered by Diffusion of Innovation (DoI) theory, which is widely used as a theoretical foundation for innovation adoption of AI. By integrating the Diffusion Innovation Theory and the Technology Adoption Rate, this study aims to fill the gap in the prior literature by examining the factors that influence the institutional level adoption of AI. Implementing the Diffusion innovation theory variable with the two external variables of Ease of Doing Business (EDB) and technology export (EXP) at the intuitive levels results in the technology adoption rate. The social component of society, where exports of technology are correlated with the public's readiness for innovation, is represented by the variable EDB. Despite the fact that AI has been studied in various fields, few research have concentrated on its importance in the educational field. Moreover, the majority of this research (Chatterjee & Bhattacharjee, 2020; Liang et al., 2021; C. Liu et al., 2021; Tyson & Sauers, 2021) assess how students' academic performance and skills are improving. Furthermore, technology exports deal with products and services that take a lot of time and money to develop new technologies for specific social needs. The Diffusion Innovation Theory and the Technology Adoption Rate hence provides a solid theoretical foundation for the alignment process.

2. Literature Review

The roles of artificial intelligence in the educational sectors and the research interest in it have been studied in earlier works. The contribution of proper models, research technique, and language skills, particularly in reading, writing, and vocabulary acquisitions, are the key areas of focus in these studies. All Natural Language Processing (NLP) systems, which aid in the development of crucial skills associated with educational settings, such as self-reflection, answering difficult questions, solving issues, and decision-making abilities, have been said to be supported by AI (Sandu & Gide, 2019). The main elements that may influence the adoption of AI include learning anxiety, willingness to interconnect, knowledge acquisition, and classroom interaction. Participants' individual traits, such as their capacity for critical thought and capacity for complicated problem-solving, may be seen as adding value to the adoption of artificial intelligence (AI). AI will have an immediate impact on decision-makers in higher education institutions (Chatterjee & Bhattacharjee, 2020; Liang et al., 2021; Liu et al., 2021; Tyson & Sauers, 2021). According to studies, when (AI) is used well in educational contexts, the general government's attitude toward using these applications changes. Since their learning styles and techniques will be enhanced on how to learn, what to learn, and when to learn it, the effectiveness in usage and execution may have an impact on teachers' and students' opinions.

One of the most important elements that promotes the adoption of AI at the school level is the enthusiasm of people who made up the sample to set up the user experience and build structural organization. The adoption of this innovation may speed up due to the advantages of AI technology. According to studies, perceived usefulness and perceived ease of use may have a positive and significant impact on adoption. The model of willingness was developed in research by Liu et al. 2021) to assess participant attitudes on the usage of AI technology in China which emphasized on the significance of key elements like perceived risk and perceived amusement variables. The findings indicate that if there is adequate support, such as sustainable development and educational belief in the significance of this invention, people are more likely to use AI technologies. The previous research examining teacher's perceptions of AI has focused on their capacity to accept and adapt to it and in the investigations, teachers at schools that had taken part in the adoption of AI applications were asked about their experiences. Teacher's AI anxiety, on the other hand, may have a negative impact on adoption because it may prevent them from employing these technologies because of their fears and concerns (Tyson & Sauers, 2021; Wang et al., 2021).

3. Theoretical framework

The interaction between the variables in the innovation diffusion theory and other macro-level variables that are essential to the adoption of innovative technology has not yet been investigated in any study. This research evaluates hypotheses that look into how students perceive the use of artificial intelligence applications in education, as well as how institutions are prepared for it and how society generally will react to it. Key components that are crucial in the adoption of new technologies at the institutional and societal levels, are perceived by DIO theory and Technology Adoption Rate. The DOI application suggests that when there are opportunities to embrace technology, the emphasis will be on the relative advantages of technology (Delrue et al., 2012). The influence of institutional factors and stakeholders on the deployment of artificial intelligence applications in the educational sector is therefore poorly understood. As a result, it is unclear from prior studies (Ukobitz & Faullant, 2022) how institutional forces affect organizational adoption of artificial intelligence.
Fig. 1 is shown below.

3.1 The diffusion of innovation theory (DOI theory)

This study incorporates the significant factor in Technology Adoption Rate to create a special framework that can account for these macro-level perspectives because one of the limitations of this theory is that it doesn't focus on additional dimensions like environmental or organizational dimensions. DOI provides a suitable method for studying the difficulties associated with the organizational adoption of innovative technology since, in contrast to TAM and UTAUT, it focuses on the context upon which the adoption choice is made. The theory looks into how to integrate novel technology into a social framework. It incorporates the factors of compatibility, trialability, and relative advantage that can significantly influence the adoption of organizational technology (Rogers, 1983). Even while the theory takes into account a variety of contextual elements, it nonetheless emphasizes the significance of technology-specific features such as relative advantage (Hsu et al., 2006; Peltier & Mizock, 2012; Teo & Tan, 2012).

The degree to which learners feel AI is a sort of technology that is superior to conventional methods and can favorably influence their future performance is therefore defined as the relative advantage in this study. Users are more likely to adopt a technology if they believe it to be compatible with their needs and experience. Perceived compatibility (CM), which is defined as the degree to which society trusts IA technologies and applications under the condition that the technology is inconsistent with the existing values, experience, and potential needs of the users, is the most important variable in the diffusion of innovation theory. As a result, this study restricts the notion of perceived compatibility to the extent that institutions and users think the IA may improve their performance to embrace the IA and boost the potentials of information systems (Venkatesh et al., 2003). On the other hand, Trialability (TB) is a measure of how much society believes that new technologies will likely be experienced. According to learners' perceptions of the acceptability of AI technology and applications, trialability measures how much future usage are encouraged and stimulated (Y.-H. Lee et al., 2011; Lou & Li, 2017). Finally, relative advantage (RA) measures how much consumers think an innovation is superior to a conventional approach. To explain the adoption of IA in the current investigation, the following hypotheses might be developed:

H_{1a}: *Perceived Compatibility (CM) affects positively ease of doing business (EDB).*
H_{1b}: *Perceived Compatibility (CM) affects positively Technology Exports (EXP).*
H_{2a}: *Trialability (TB) affects positively ease of doing business (EDB).*
H_{2b}: *Trialability (TB) affects positively Technology Export (EXP).*
H_{3a}: *Relative Advantage (RE) affects positively ease of doing business (EDB).*
H_{3b}: *Relative Advantage (RE) affects positively Technology Export (EXP).*

3.2 Ease of doing business (EDB)

Business growth is made possible by the company's willingness to support the usage of technology. People are more inclined to adopt new technology if they believe doing business is simple (Babatunde et al., 2021). EDB is a crucial marker that reveals the ideal setting for enhancing new technologies and also a key element that influences how willing a population is to adopt innovation. It is a distinctive statistic that shows how macro-level institutions can manage significant business difficulties. It is hypothesized, based on the prior deduction, that:

H_{11}: *The Ease of doing business (EDB) has a positive impact on the adoption of AI (AIA).*

3.3 Technology Exports (EXP)

Recently, societies have seen a movement toward high-technology exports, which are new technologies that are produced in rich economies but dispersed and sold to less developed countries. The technology export variable is an outside factor that affects how technology adoption is measured. Exports of technology deals with products and services that need substantial research and funding to develop new technologies in response to societal requirements. It could contain a variety of things, ranging from instrumentation and electrical equipment to technical support and innovation (Szalavetz, 2019). Therefore, receptive countries are those that are less used to the spread of technology infusion (Szalavetz, 2019). As a result, it is hypothesized that:

H_{12}: *The technology export (EXP) of a country has a positive impact on the adoption of AI (AIA).*

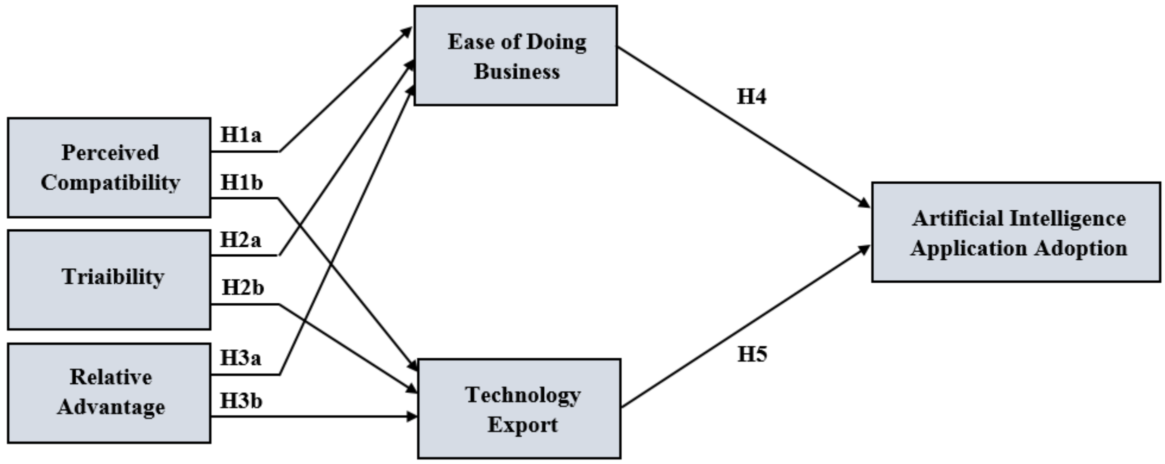

Fig. 1. Proposed research model.

4. Research Methodology

4.1 Sample and data collection procedure

The study team utilized structural equation modeling (SEM) (SmartPLS Version 3.2.7) to evaluate the measurement model. The final path model was used to carry out advanced therapy. Between April 10, 2022, and June 25, 2022, data collection was done. Online surveys were given to participating students from the universities in the UAE. 400 questionnaires were randomly distributed by the research team and a 97% response rate was achieved from these surveys, which makes it 387 questionnaires, in addition to the 13 surveys which were also disqualified due to some missing data. As a result, there were 485 usable questionnaires. The sample size (387) and the minimal needs are very dissimilar. It's also important to note that our ideas were built on the preceding theories (based on the context of digital information). According to (Krejcie & Morgan, 1970), the sample size for these accepted questionnaires (the anticipated sampling size for 306 respondents/1500 population) was at the proper level. Given this, the sample size may be the results of the structural equation modeling analysis (Chuan & Penyelidikan, 2006), which were then utilized to verify the hypotheses.

4.2 Students' personal information / Demographic Data

According to Al-Emran and Salloum (2017), "purposive sampling technique" can be used when respondents indicate a readiness to volunteer. In Table 1, the demographic and personal information has been assessed. Most of the respondents were educated and held university degrees. More precisely, 76%, 19%, and 5% of students had bachelor's degrees, master's degrees, or doctorate degrees, respectively. Regarding this sample, the students came from various universities, age groups, and educational levels. 79% of respondents were between the ages of 18 and 29; the remaining respondents were older than 29. There were also 64% female pupils and 36% male students. Other than that, demographic data were measured using IBM SPSS Statistics version 23.

Table 1
Demographics of the respondents (n= 387)

Demographics	Factor	Frequency	Percentage
Gender	Female	249	64%
	Male	138	36 %
Age	Between 18 to 29	305	79%
	Between 30 to 39	67	17%
	Between 40 to 49	11	3%
	Between 50 to 59	4	1%
Education qualification	Bachelor	295	76%
	Master	72	19%
	Doctorate	20	5%

4.3 Study Instrument

Seventeen new items have been added to the survey in order to offer the exact measurement tools required to measure the questionnaire's 6 components and the survey tool was employed to verify the hypothesis in the current study. The researchers modified the study questions from earlier studies. The source of these constructs which makes the research constructs more usable and provides evidence from the body of literature already in existence to support the current model is shown in the table below.

Table 2
Construct measures

Constructs	Items	Instrument	Sources
Artificial Intelligence Application Adoption	AIA1	Institutions are prepared to use AI technology in their educational programs.	(Hooks et al., 2022)
	AIA2	Institutions are prepared to modernize their educational platforms and use AI in them.	
Perceived Compability	CM1	The existing educational system is compatible with AI technology.	(Venkatesh et al., 2003)
	CM2	The learning styles and teaching methods are compatible with AI technology.	
	CM3	AI is incompatible with the existing educational framework.	
Trialability	TB1	Future applications are possible thanks to AI technology.	(Y.-H. Lee et al., 2011; Y. H. Lee, 2007)
	TB2	Future educational activities can be assessed with the aid of AI technology.	
	TB3	Because it offers opportunities for rich material in educational settings, AI is innovative.	
Relative advantage	RE1	Compared to previous technologies, AI offers more educational functions.	(Y.-H. Lee et al., 2011; Y. H. Lee, 2007)
	RE2	In comparison to the previous method, AI technology allows me to save time and effort.	
	RE3	The use of AI in education is incompatible with present educational models.	
Ease of Doing Business	EDB1	At the institutional level, artificial intelligence is broadly recognized.	(Babatunde et al., 2021)
	EDB2	Many users of AI in modern culture are familiar with the technology.	
	EDB3	Students and academic staff favor AI technology.	
Technology Export	EXP1	IA technology was created by other nations and suits societal demands.	(Szalavetz, 2019)
	EXP2	At the institutional level, demand is considerable for AI technology innovation characteristics.	
	EXP3	The requirements of the academic personnel are not met by IA technology.	

4.4 Common method bias (CMB)

The newly generated component accounts for 24.37% of the variation, which is less than the required amount of 50% (Podsakoff et al., 2003), according to the analysis. Harman's single-factor analysis has been performed with seven components to guarantee that the collected data do not include CMB (Podsakoff et al., 2003). Then, the 10 factors were combined into one factor. Therefore, there were no issues with the CMB in the data that were gathered.

4.5 Pilot study of the questionnaire

Using IBM SPSS Statistics version 23's Cronbach's alpha test for internal reliability, the results of the pilot study were more thoroughly analyzed. The Cronbach's alpha values are shown in Table 3 in relation to the following 5 measurement scales. A pilot study was done to evaluate the validity of the survey's questions. This approach aids in the process of producing valid results for the measurement items. The data were chosen at random and were based on the fact that 40 pupils from the demographic that was chosen for this pilot study were included in the selection. 400 students were chosen as the sample size while keeping in mind that 10% of the overall sample size for the analysis, and for this, stressing the research guidelines. It is deemed appropriate to have a reliability coefficient of 0.70 when taking into account the indicated trend in social science research (Nunnally & Bernstein, 1978).

Table 3
The pilot study (Cronbach's alpha)

Construct	Cronbach's Alpha
AIA	0.760
CM	0.826
EDB	0.811
EXP	0.872
RE	0.725
TB	0.883

4.6 Survey Structure

Three separate sections make up the questionnaire survey, which was given to a group of students (Al-Emran & Salloum, 2017).

- The respondents' personal information is closely related to the first component.
- The so-called "Artificial Intelligence Application Adoption" is illustrated by two things in the second section.
- The final component has 15 items that are divided into the following categories: Trialability, Perceived Compatibility, Relative Advantage, and Ease of Doing Business.

A five-point Likert scale with the five possible responses of strongly disagree (1), disagree (2), neutral (3), agree (4), and strongly agree (5) has been used in order to effectively measure the 17 elements.

5. Analysis and Results

5.1 Measurement model

A two-stage evaluation process using the structural model and measurement model has been used to analyze the acquired data (Hair et al., 2017). There are various justifications for the usage of The Partial Least Squares-Structural Equation Modeling (PLS-SEM) tool in this investigation, with assistance from the SmartPLS V.3.2.7 program, which were both used for data analysis in this paper (Ringle et al., 2015).

PLS-SEM is used as it provides concurrent analysis for measurement and structural model, enabling us to use it to produce correct calculations (Barclay et al., 1995). Secondly, rather than disassembling the entire model, PLS-SEM evaluates it as a whole (Goodhue et al., 2012). Thirdly, PLS-SEM functions best when the investigation is built upon prior research or study (Urbach & Ahlemann, 2010). Lastly, exploratory investigations using complicated models can effectively apply the PLS-SEM (Hair Jr et al., 2016).

5.2 Convergent validity

According to Table 4, Cronbach's alpha (CA), which measures construct dependability, was shown to be between 0.795 and 0.899. These numbers are lower than the cutoff value (0.7) (Nunnally & Bernstein, 1994). Table 4's findings indicate that the composite reliability (CR) values vary from 0.811 to 0.889, above the cutoff point (Kline, 2015). (Hair et al., 2017) proposed using the construct reliability (which include Cronbach's alpha (CA) and composite reliability (CR)) and validity (which includes discriminant and convergent validity) to evaluate the measurement model.

Table 1 shows the AVE values, which are considered to be greater than the '0.5' threshold value ignoring the prior values, ranging from 0.656 to 0.731. Apart from the ones already stated, the table (4) below demonstrates that each factor loading value is above the cutoff value of 0.7. It is likely to achieve convergent validity as a result of the earlier explanation. Testing the mean variance extracted (AVE) and factor loading is crucial for determining how well convergent validity is being measured (Hair et al., 2017).

5.3 Discriminant validity

Data in table 5 show that the Fornell-Larker condition confirms the criteria since each AVE and its square roots have higher correlations with other components than expected (Fornell & Larcker, 1981), hence, it was advised to revisit two criteria based on the Heterotrait-Monotrait ratio (HTMT) and the Fornell-Larker criterion since the study aimed to test the discriminant validity (Hair et al., 2017).

The analysis's findings showed that there were no problems whatsoever with evaluating the measurement model's validity and reliability. As a result, the data gathered may also be utilized to assess the structural model. The presence of HTMT ratio shown in Table 6, indicates that each construct's value is less than the '0.85' threshold value (Henseler et al., 2015). These conclusions allow for the computation of the discriminant validity.

Table 4
Convergent validity results.

Constructs	Items	Factor	Cronbach's Alpha	CR	AVE
Artificial Intelligence Application Adoption	AIA1	0.726	0.889	0.873	0.731
	AIA2	0.872			
Perceived Compability	CM1	0.825	0.899	0.889	0.703
	CM2	0.912			
	CM3	0.903			
Trialability	TB1	0.876	0.891	0.827	0.656
	TB2	0.891			
	TB3	0.820			
Relative advantage	RE1	0.825	0.884	0.811	0.706
	RE2	0.818			
	RE3	0.829			
Ease of Doing Business	EDB1	0.821	0.868	0.851	0.705
	EDB2	0.833			
	EDB3	0.891			
Technology Export	EXP1	0.756	0.795	0.877	0.722
	EXP2	0.867			
	EXP3	0.892			

Table 5
Fornell-Larcker Scale

	AIA	PC	TB	RE	EDB	EXP
AIA	**0.887**					
PC	0.591	**0.797**				
TB	0.462	0.499	**0.864**			
RE	0.262	0.396	0.412	**0.806**		
EDB	0.323	0.486	0.290	0.522	**0.867**	
EXP	0.591	0.539	0.215	0.626	0.326	**0.890**

Table 6
Heterotrait-Monotrait Ratio (HTMT)

	AIA	PC	TB	RE	EDB	EXP
AIA						
PC	0.702					
TB	0.035	0.094				
RE	0.459	0.507	0.480			
EDB	0.543	0.608	0.470	0.224		
EXP	0.527	0.502	0.309	0.330	0.634	

5.4 Hypotheses testing using PLS-SEM

Each path's variance description (R^2 value) and each connection's path relevance in the study model were evaluated. Fig. 2 and Table 8 show the standardized path coefficients and path significances. The combined testing of the nine aforementioned hypotheses was conducted using the structural equation modeling (SEM) method (Davis et al., 1992).

The empirical data supported the hypotheses H1a, H1b, H2a, H2b, H3a, H3b, H4, and H5 based on the data analysis. According to Table 7, the R^2 values for Technology Export, Ease of Doing, and Artificial Intelligence Application Adoption varied from 0.696 to 0.735. As a result, these structures seem to have strong predictive ability (Liu et al., 2005). Perceived Compability (CM), Trialability (TB), and Relative Advantage (RE) has significant effects on Ease of Doing Business (EDB) (β= 0.728, P<0.001), (β= 0.566, P<0.05), and (β= 0.460, P<0.05), respectively; hence H1a, H2a, and H3a are supported. The findings also revealed that Technology Export (EXP) significantly influenced Perceived Compability (CM) (β= 0.803, P<0.001), Trialability (TB) (β= 0.395, P<0.05), and Relative Advantage (RE) (β= 0.773, P<0.001) supporting hypothesis H1b, H2b, and H3b respectively. The relationships between Ease of Doing Business (EDB), and Technology Export (EXP) has significant effects on Artificial Intelligence Application Adoption (AIA) (β= 0.634, P<0.001), and (β= 0.647, P<0.001) respectively; hence H4, and H5 are supported.

Table 8
R^2 of the endogenous latent variables

Construct	R^2	Results
AIA	0.696	High
EDB	0.735	High
TB	0.704	High

Table 9
Results of hypothesis testing

H	Relationship	Path	*t*-value	*p*-value	Direction	Decision
H1a	CM → EDB	0.728	9.587	0.003	Positive	Supported**
H1b	CM → EXP	0.803	11.35	0.001	Positive	Supported**
H2a	TB → EDB	0.566	4.532	0.043	Positive	Supported*
H2b	TB → EXP	0.395	5.71	0.037	Positive	Supported*
H3a	RE → EDB	0.46	6.113	0.028	Positive	Supported*
H3b	RE → EXP	0.773	15.682	0	Positive	Supported**
H4	EDB → AIA	0.634	18.083	0	Positive	Supported**
H5	EXP → AIA	0.647	14.544	0	Positive	Supported**

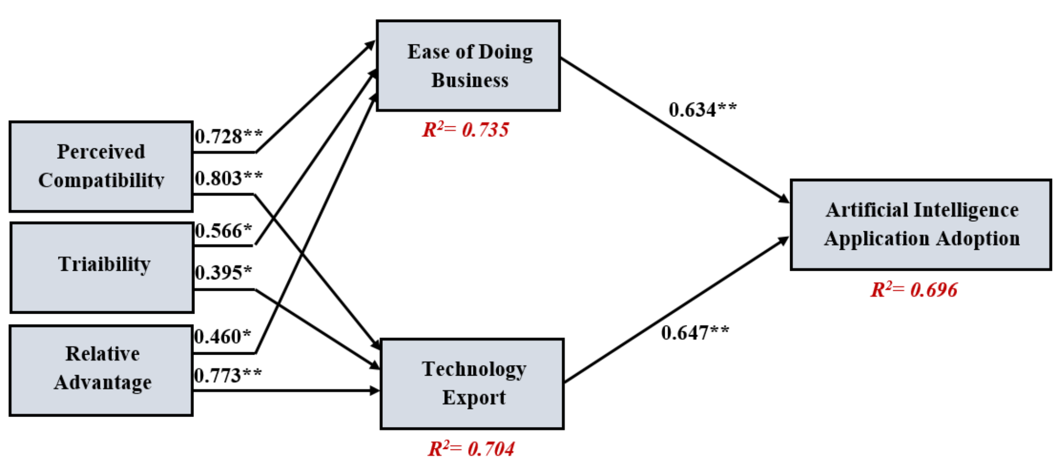

Fig. 2. Path test of the research model (*Note.* **p*<.05 ***p*<.01).

6. Discussion of Results

The diffusion theory, which consists of a number of independent variables, proposes a model for adoption and determines the degree to which these variables might influence the adoption of AIA. The results of the study have demonstrated that Technology Export (EXP) and Ease of Doing Business (EDB) both have a direct impact on adoption. This study's main goal was to assess how artificial intelligence (AI) applications were being used in educational settings. In our effort to achieve this goal, two key factors were identified that served as the project's direction. When compared to other independent factors, ease of doing business and technology export is particularly important in identifying and influencing the adoption of Artificial Intelligence applications. Similar to this, the current literature on the effectiveness of technology export has focused on the fact that technical exports comprise products and services that required considerable development time and funding. Technology innovation might comprise electrical instruments and equipment in addition to technical assistance and invention. All of these factors have a role in the AIA's adoption in terms of technology export. The current results are at odds with earlier studies, which demonstrate that EDB has a significant influence on the adoption of technology. Because of EDB, it is possible to determine what kind of setting is best for advancing new technologies. EDB significantly increases people's willingness to adopt innovation. With the use of this special assessment, institutions may demonstrate their capacity to manage important business difficulties. When businesses are ready to use technology, they succeed. Thus, the notion that conducting business is simple indicates that people will more quickly adopt new technology.

Statistical analysis uncovered many important insights that helped achieve the study's goal. The results of the statistical research have revealed a substantial association between the various conceptual model variables. Perceived compatibility, trialability, and relative advantage are the additional three variables that might link with the first three described above.

It is more crucial for people to think that innovations will help them than it is for them to realize that they are superior to existing practices. The diffusion of innovation theory states that an innovation will spread more quickly the better its perceived relative advantage. According to (Ntsiful et al., 2022), perceived value and an innovation's relative advantage are strongly connected. (John, 2016) asserts that relative advantage awareness, accessibility, user-friendliness, service quality, network dependability advantage, and convenience are all related to technology adoption. First, "perceived compatibility, trialability, relative advantage" and ease of conducting business have a striking relationship. The government can function more effectively whenever technology satisfies their demands without more difficulty, according to this favorable association.
According to a research by (Oliveira et al., 2014), incompatible innovations are less likely to be accepted than compatible ones, indicating that they require a pushing function to get past obstacles and seize chances. According to the results, compatibility and AIA have a close relationship. Compatibility was discovered to be the main factor influencing technology (Lubanga et al., 2017; Nezamdoust et al., 2022). In light of this, compatibility may be used as an independent variable to help determine the degree of adoption at the governmental level, acting as an early warning system for its high relevance (Alam et al., 2022; Erdener et al., 2022).

6.1 Theoretical and Practical implications

The current study contributes to the body of knowledge by confirming the findings of other studies about the effectiveness of diffusion theory. It also adds to the body of theoretical knowledge by demonstrating that diffusion theory and related factors have a favorable impact on the ease of doing business and technology export in the AIA. The theoretical conclusion is that educational institutions have a high level of confidence in the function of AI and have technology readiness in this area. The outcome of this discovery is that users in the education sections are encouraged to utilize AI and to have a positive mindset and a willingness to keep using it.

The willingness and trust of users may be strongly impacted by the ease of doing business and the technology export. The utilization of AIA is improved by these two factors. The adoption rate for AI can be increased if the developers of these applications can be persuaded to have more compatible features. Similar to this, a higher degree of adoption intention was produced by the positive relationship between trainability and relative advantage, which changed the way people traditionally viewed educational institutions and helped create a more developed and accessible system. As a result, application developers and programmers should think about adding more tools and ways to engage the users, as well as proposing features that differ from the traditional tools used in all educational institutions. These tools can be employed as teaching techniques to open the door for a future system that is more inventive. The success that may be accomplished in providing services at the educational level has practical implications. By making explicit information about the implementation process available via official websites and marketing, the system may be developed.

6.2 Managerial Implications

AIA is regarded as an innovative technology that may improve people's quality of life and personal growth. The head of education should push for AIA adoption in their education institutions. The proposed elements that aid in promoting awareness of the significance of AI at the educational level should be reshaped by application developers. Based on the study's findings, the educational sectors can benefit from the managerial implications, which will enable more innovative AIA implementation.

The results have shed further light on the idea that innovation and development are essential components of education. The new research can help managers and developers deal with issues like complexity and difficulties that may occur from employing AI, which have a detrimental impact on physical discomfort and safety of the adoption.

7. Conclusion

According to the study's findings, the DOI hypothesis has a useful metric linked to compatibility, trialability, and relative benefit. They have an impact on the acceptance of AIA in educational institutions. Furthermore, compatibility has a significant influence on the ease of doing business and technology export. Adopters are more inclined to view innovation as being compatible with their way of life, which accounts for its high effect. The users will greatly profit from the development of the technology if AIA satisfies the requirements of the government's goals and as a result, consumers may easily modify and replace an existing good or concept. Adoption of AIA will open up new perspectives on how technology is used in many governmental sectors, resulting in significant savings and advantages from increased productivity. The government will be more eager to use AIA, offering more cutting-edge features that will provide educational sectors solutions and the potential for future growth. In order to improve future development and planning, the research concludes by recommending the usage of AI in various governmental agencies. Additionally, this study came to the conclusion that trialability, which is essential for aiding adoption, has a tremendous influence on AIA adoption. This is a result of consumers wanting to test out AIA before purchasing it and see what it is capable of. Future research may include more variables that support the aims and objectives of users while concentrating on the analysis of elements impacting AI adoption intentions. Future research may use other ideas to provide findings that complement the ones now being done but the present study contains a lot of restrictions. The first drawback is that the research model is restricted to a selection of factors that are used as measuring sticks for the impact of AIA. Furthermore, it is not feasible to assert that our findings are generalizable because the research evidence for our study was limited to a particular country and further research in different contexts would be required to confirm our findings in order to gain a deeper understanding of this topical and important subject. Finally, our study has shed light on the DOI theory's applicability to AIA by governments in developing nations.

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