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Exploring the integration of artificial intelligence in education: An empirical study utilizing a hybrid SEM-ML

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A B S T R A C T

Artificial intelligence is user-friendly and incorporates a useful number of characteristics that are common across the various services that are provided. By enhancing inventive engagement, artificial intelligence (AI) applications enable a more participatory setting in government agencies. The objective of this research is to find out how the UAE consumers feel about using AI in educational settings. Included in the framework are the characteristics of acceptance, which are: perceived compatibility, trialability, relative advantage, ease of doing business, and technology export. 466 questionnaires from various universities have been gathered. The research model was examined using machine learning algorithms (ML) and partial least squares-structural equation modeling (PLS-SEM), which centered on the student's questionnaire responses. The IPMA is also used in this research to evaluate performance and importance of the variables. The theoretical framework of the research links the qualities of the individual variables and those of the technology which makes it new. The findings indicate that the diffusion theory factors outperform the other two factors of ease of doing business and technology export. It ought to be mentioned that when it pertains to the estimated value of the dependent factor, the J48 classifier largely outperformed other classifiers. This study's findings can guide educational institutions in the UAE to recognize the importance of each acceptance factor in the successful integration of AI technologies. Institutions can use these insights to tailor their strategies, enhancing AI adoption among students and faculty alike. Specifically, the results suggest prioritizing factors from diffusion theory in educational AI implementations, ensuring these technologies are perceived as advantageous and compatible with existing practices. Furthermore, the superiority of the J48 classifier suggests that similar analytical techniques could be employed by educational institutions to continually assess and improve their AI initiatives. The dominance of diffusion theory factors invites further exploration into how these elements specifically influence AI acceptance in other sectors or regions. Additionally, the comparative underperformance of ease of doing business and technology export as factors suggests a need for deeper investigation into how these dimensions can be better leveraged in the context of AI in education. Future research could also explore longitudinal studies to assess the sustainability of AI acceptance over time and experiment with integrating new machine learning algorithms to compare their predictive power against the J48 classifier in different educational settings.

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1. Introduction

AI Applications that employ machine learning have been widely used in multiple contexts, most importantly the clinical, agricultural, digital transformation (Al-Emran & Salloum, 2017; Nawaz et al., 2024), and in educational research. Such applications are promising in the previously mentioned contexts. Both technology developers and scholars studying foreign languages in education are interested in AI approaches (Strauss et al., 2024). However, there remains a lack of data and conflicting findings when it comes to the real effects of AI on the writing abilities of learners. On an institutional level, the application of AI is only partly ignored. In conclusion, some obstacles prevent precise deployments, useful results, and better achievements while using AI in educational contexts (Liang et al., 2021).

The success of learning, the areas of learning, and the approaches to learning are all significantly impacted by artificial intelligence. One positive impact of AI applications in pedagogical institutions is the level to which a lesson can be considered useful. When schools and communities uphold the importance of blending such innovative applications into the educational setting, learner engagement will increase (Al-Emran et al., 2018, 2021). The perception of enjoyment, satisfaction, and institutional assistance, together with the assumption of usefulness and comparative benefit, should all be present for the pupils to be engaged in a smart teaching environment (Liu et al., 2021). In some nations, the kind of hardware and software utilized in the classroom has an impact on learners' willingness to accept new innovative technologies. Other factors that significantly affect students' views regarding adopting new technologies are the possibility of reduced learning anxiety, a willingness to adopt them, and knowledge accumulation. Additionally, the learners' individual qualities are crucial. Potential adoption of state-of-the-art AI apps may be eased through learners' skills, such as problem-solving and critical thinking (Chatterjee & Bhattacharjee, 2020).

Even though AI has been studied in various fields, a handful of publications focused upon its pedagogical significance. The Diffusion of Innovation (DoI) theory, which is widely used as the conceptual foundation for the innovative adoption of AI, covers fundamental innovation components, adopters, and communication routes. The prior research's main objective was to create an idea of adoption at the micro-level. The present research, nevertheless, attempts to come up with a model that takes ingenuity into account by including it within the Technology Adoption Rate, wherein organizational views are considered to account at the micro-level. Applying the diffusion innovation theory factor with the two separate exogenous factors of ease of doing business (EDB) and technology export (EXP) at the intuitive stages results in the technology adoption rate. The social component correlates with societal innovation willingness, and is represented by the factor EDB. Additionally, technology exports encompass products and solutions which require effort as well as finances to come up with new technologies for particular societal requirements. The Diffusion Innovation Theory and the Technology Adoption Rate thus provide a sound conceptual basis for the synchronization phase. The undeniable influence of AI in multiple contexts such as the medical context, the agricultural context, and the engineering context has been the focus of prior studies (Varghese, 2020). Additionally, most of this research (Ukobitz & Faullant, 2022) assesses how students' academic performance and abilities are improving. In opposition to past research, this study tries to investigate the macro-level adoption of AI through combining the Diffusion Innovation Theory and the Technology Adoption Rate. It attempts to bridge the gap in research by looking into the factors which affect how and why organizations adopt Artificial Intelligence. The structural equation modeling (SEM) technique is frequently used in the Diffusion Innovation Theory and Technology Adoption Rate to evaluate hypotheses (Wang et al., 2017, 2021). Additionally, it planned to validate the research model employing Partial Least Squares (PLS)-SEM and machine learning (ML) algorithms.

The impetus for this study arises from the rapid integration of artificial intelligence (AI) in educational contexts and the pressing need to understand how such technologies are received by users. As educational institutions in the UAE increasingly adopt AI, there is a critical need to evaluate which factors influence acceptance and successful implementation. This research aims to identify these factors by investigating UAE students' perceptions towards AI in education. By doing so, we seek to provide actionable insights that can help tailor AI integration strategies to enhance learning experiences, improve educational outcomes, and ensure that AI adoption aligns with the needs and expectations of the student body.

2. Literature Review

Prior studies have focused on both the utilization of AI in pedagogical institutions and the academic devotion to it. All-Natural Language Processing (NLP) systems that assist in the improvement of essential capabilities related to learning environments, including reflective thinking, addressing challenging inquiries, problem-solving, and decision-making abilities can be enhanced by AI (Zheng et al., 2021). The impact of fitting models, empirical techniques, and language acquisition aspects (reading, writing, and vocabulary development) are emphasized. The significance of learning anxiety, communicative willingness, knowledge acquisition, and classroom interaction can affect the adoption of AI. Individuals' traits, including their capacity for analytical reasoning and capacity for complicated problem-solving, could potentially be seen as adding significance to the adoption of artificial intelligence (AI). Findings suggest that using (AI) in pedagogical contexts changes the government's broad perception of applications of these technologies' changes. Since their learning modes and methods are going to be enhanced regarding the way and the timing of learning, the efficacy in application and execution may influence instructors' and students' opinions. AI has a direct influence on those responsible for college-level education facilities (Alsheibani et al., 2019).

Earlier studies have asked instructors in classrooms who had taken an active role adopting AI apps for comments and notes. The element which arguably best enhances embracing AI in primary and secondary stages is how enthusiastic are the individuals in the study population to establish both their environment and a hierarchical management. Prior research addressing educators' perspectives of AI emphasized their willingness to embrace and adjust to it. The advantages of AI technology may hasten the adoption of this innovation. Research indicates that perceived usefulness and perceived ease of use can positively affect adoption. On the other hand, instructors' AI anxiety may harm the process of adopting this technology since it hinders them from using such innovations as a result of dread and worries (Tyson & Sauers, 2021). The concept of willingness was developed in research by (Malik et al., 2019) to assess the views of respondents regarding the application of AI technology in China. The model emphasizes the importance of vital factors such as perceived risk and perceived entertainment elements. Results also indicate that the existence of adequate assistance (equitable growth and academic confidence in the importance of such innovation) make individuals more inclined to adopt AI technologies.

PLS-SEM and the ML algorithm are two methodologies used in the current study to evaluate conceptual models. PLS-SEM allows simultaneous measurement and structural model analysis, claim Ringle, Wende, and Becker (2015). According to Barclay et al. (1990), the outcomes of PLS-SEM simultaneous evaluation are valuable insights. The current study also makes use of an ML algorithm via SPSS (Davis, 1989) to ascertain the relationships between the variables in the research model. The current research used decision trees, Bayesian networks, and neural networks in the ML algorithm to predict the relationship between features in the model (Davis, 1989). Weka was implemented in the research to evaluate the model, which was built using predictors like OneR, Logistic, LWL, J48, and BayesNet.

Most publications have employed one-stage linear data analysis (Sohaib et al., 2019), mainly using the SEM, to predict the relationship between factors. The linear correlation between each factor in the models has been the subject of previous studies. Sim et al. (2014) contend that the method of decision-making may not be predicted by the linear correlation between factors. Researchers Leong et al. (2013) and Khan and Ali (2018) suggested the Artificial Neural Network (ANN) analysis as a second-stage analysis to address the drawbacks of SEM's single-stage data analysis approach. Huang and Stokes (2016) counter that the deep subtype ANN with only one hidden stage is typically used in the study. The research by Wang et al. (2017) suggests using deep ANN or ANN having multiple layers to increase the accuracy of non-linear models. The current work analyses the data concerning the suggestions employing deep ANN, a hybrid SEM-ANN technique.

3. Theoretical framework and hypothesis development

Technology adoption and the DIO theory briefly assess the following important factors that are crucial to the organizational and societal adoption of new technology. The Given DOI applicability indicates that whenever the chances are there for adopting technology, the focus is going to be on the possible benefits of technology (Wang et al., 2017). However, prior research (Ukobitz & Faullant, 2022) is not definitive on how organizational factors affect the organizational adoption of artificial intelligence. How organizational variables exactly affect the adoption of artificial intelligence applications in educational institutions is not clear. The link between variables in the innovation diffusion theory and other macro-level variables vital to embracing innovative technology is still missing. As a result, the current study assesses hypotheses that investigates the way learners recognize the use of AI applications in education, the way schools are equipped to adopt them and how society may accept them. Figure (1) is shown below.

3.1 The diffusion of innovation theory (DOI theory)

DOI proposes a way for analyzing the problems related to the institutional embracing of new technology since, unlike TAM and UTAUT, it emphasizes the conditions related to how to choose a technology. The theory investigates the way to combine new technologies within a social structure and the factors of compatibility (trialability, and relative advantage) which notably affect how and why institutions adopt technology (Malik et al., 2019). In spite of the fact that this theory takes into account many contextual variables, it highlights the importance of technology-specific characteristics like relative advantage (Sandu & Gide, 2019). This theory has some drawbacks, one of which is that it does not emphasize extra aspects like contextual or institutional variables. To provide a special model that will allow for such macro-level viewpoints, the present research adds the important aspect of the Technology Adoption Rate.

People will easily adopt a technology once it is clear to them that such technology suits their needs and perspective. Perceived compatibility (CM) is influenced by the public confidence in AI technologies and applications, experience, and future requirements of the consumers, and is a significant parameter in the diffusion of innovation theory. This current research limits the notion of perceived compatibility to the level to which organizations and customers believe that AI can enhance their ability to adopt AI and boost future possibilities of information systems (Alsheibani et al., 2019). Trialability (TB) is the measure of how users perceive AI technology and applications to be motivating and inspiring new applications (Tyson & Sauers, 2021). Relative advantage (RA) estimates the level to which people believe an innovation is better than what they are accustomed to use. The extent to which students perceive AI as a better technology which can positively affect their prospective output is thus described as the relative advantage in this study. The following hypotheses have been developed in order to elucidate the adoption of AI in this current study:

H$_1$: *Perceived Compatibility (PC) predicts the Ease of doing business (ED).*

H$_2$: *Perceived Compatibility (PC) predicts the Technology Export (TE).*

H$_3$: *Observability (OB) predicts the Ease of doing business (ED).*

H$_4$: *Observability (OB) predicts the Technology Export (TE).*

H$_5$: *Triaibility (TR) predicts the Ease of doing business (ED).*

H$_6$: *Triaibility (TR) predicts the Technology Export (TE).*

H$_7$: *Relative Advantage (RA) predicts the Ease of doing business (ED).*

H$_8$: *Relative Advantage (RA) predicts the Technology Export (TE).*

3.2 Ease of doing business (EDB)

EDB is an important factor affecting how ready a group of people is to accept new technology. EDB is a crucial marker which reveals the ideal setting for enhancing modern technology as well as uniquely showing the way organizations at the macroeconomic level can manage major company challenges. The organization's readiness to adopt and use technology ensures business growth. Customers can be more prepared to embrace innovative technology once they are assured of the simplicity of running a business using such technology (Chatterjee & Bhattacharjee, 2020). Hence, it is hypothesized that:

H$_9$: *Ease of doing business (ED) predicts the behavior intention to use AI (IN).*

3.3 Technology Exports (EXP)

Technology Exports involve commodities and solutions which require real study and financing to build novel technologies that answer social demands. This covers aspects like instrumentation, electrical devices, technological assistance and inventiveness (Nawaz et al., 2024). Recently, there has been a rise in favoring high-technology exports; novel technologies created in rich economies but disseminated and sold to poorer economies that are less accustomed to such technology and its introduction (Nawaz et al., 2024). Technology exports can be considered an outside factor influencing the way technology is adopted and estimated. Therefore, it is hypothesized that:

H$_{10}$: *Technology Export (TE) predicts the behavior intention to use AI (IN).*

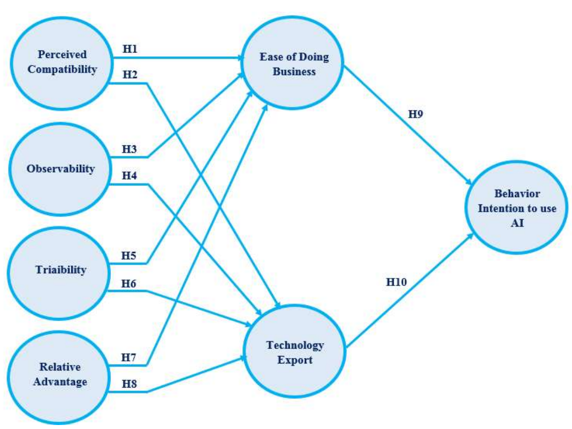

Fig. 1. Research Model.

4. Research Methodology

4.1 Data collection

Online surveys were given to collaborating students from universities in the UAE. From February 10, 2023, to May 10, 2023, data was collected. The study committee distributed 500 questionnaires arbitrarily. A 93% response rate was achieved from the surveys, with participants completing 466 questionnaires. An additional 34 questionnaires were excluded due to incomplete data, leaving 466 valid questionnaires. Based on Krejcie and Morgan (1970), this sample size (466 questionnaires) exceeded the required level for the expected sample size of 306 respondents from a population of 1,500 (Chuan & Penyelidikan, 2006). The sample size (466) significantly exceeded the minimum requirement. Therefore, structural equation modeling (SEM) as outlined by Sohaib et al. (2019) was deemed suitable for supporting the hypotheses. It's worth noting that our hypotheses were grounded in previous research, drawing from the historical context of AI. The academic team employed Structural Equation Modeling (SEM) using SmartPLS Version 3.2.7 to evaluate the measurement model. The final path model was then used for conducting advanced analyses.

4.2 Students' personal information / Demographic Data

In Fig. 2, the demographic and personal information has been assessed. Furthermore, 55% of the learners were female and 45% were male. In addition, 54% of the participants were between the ages of 18 and 29 and the remaining participants were older than 29. Most of the participants were qualified and held university degrees. 68%, 26%, and 6% of those surveyed held B.A., M.A., and PhD correspondingly. In situations where participants express a readiness to volunteer, the "purposive sampling approach" may be used, according to Salloum and Shaalan (2019). Participants in this study were from different universities, of different ages, and have different levels of education. Additionally, IBM SPSS Statistics version 23 was utilized for evaluating the demographic data.

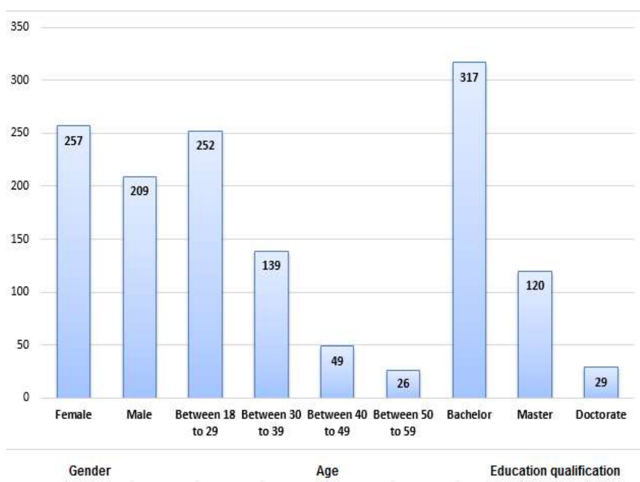

Fig. 2. Demographic data of the respondents (n= 466).

4.3 Study Instrument

In the present research, a questionnaire was utilized to authenticate the hypothesis. Seven constructs in the questionnaire have been effectively chosen as the reliable measuring way, consequently, 17 new items were included in the questionnaire. The basis of these constructs is shown in the table beneath, which is provided to render the study constructs more usable and to provide proof from a variety of research already in existence that reinforces the present framework. Lastly, the academics modified the survey questions from earlier studies.

Table 1
Measurement Items

Constructs	Items	Instrument	Sources
Behavior intention to use AI	IN1	Schools are ready to integrate AI technology into their curricula.	(Nawaz et al., 2024)
	IN2	Schools are ready to deploy AI to update their systems of instruction.	
Observability	OB1	Other organizations consider AI to be effective and educational.	(Strauss et al., 2024)
	OB2	The faculty views AI as a beneficial way for creating a teaching-learning setting.	
	OB3	The neighboring nations classify AI technology as cutting-edge technology.	
Perceived Combability	PC1	The current instructional framework is interoperable with AI.	(Strauss et al., 2024)
	PC2	The instructional approaches and learning approaches are compatible with AI technology.	
	PC3	AI contrasts with the system for schooling that is now in place.	
Trialability	TR1	Prospective applications are made conceivable by AI technology.	(Liu et al., 2021)
	TR2	Using AI technology, the next academic initiatives can be evaluated.	
	TR3	AI is revolutionary as it provides possibilities for rich content in classrooms.	
Relative advantage	RA1	AI has more instructional features than the earlier technology.	(Liu et al., 2021)
	RA2	I can conserve a lot of time relative to the prior way thanks to AI technology.	
	RA3	AI in classrooms is incompatible with the current academic paradigms.	
Ease of Doing Business	ED1	The organization level has a higher rate of acceptance for AI.	(Ukobitz & Faullant, 2022)
	ED2	In contemporary society, AI is widely used and well-known.	
	ED3	Educational professionals as well as learners prefer AI technology.	
Technology Export	TE1	Various countries have developed AI technology, which satisfies social requirements.	(Ukobitz & Faullant, 2022)
	TE2	There is a substantial institutional need for the features associated with innovative AI technology.	
	TE3	The needs of instructors are not satisfied by AI technology.	

4.4 Common method bias (CMB)

Harman's single-factor analysis was conducted using seven variables to ensure that the collected data did not contain common method bias (CMB) (Sim et al., 2014). Subsequently, ten factors were loaded into a single factor. The analysis revealed that the newly created factor accounted for 23.49% of the total variance, which is below the threshold value of 50% (Sim et al., 2014). Therefore, no concerns regarding CMB were identified in the collected data.

4.5 Pilot study of the questionnaire

To assess the reliability of the survey questions, a pilot study was conducted. The data were randomly selected, focusing on a sample of 40 students from the target demographic for the pilot. The main study involved 500 students, with 10% of the total sample size allocated for the pilot evaluation. The pilot study's results were analyzed using Cronbach's alpha in IBM SPSS Statistics version 23 to measure internal reliability, helping to ensure robust findings for the measurement items. A reliability coefficient of 0.70 is considered adequate for social sciences research (Sim et al., 2014). Table 2 presents Cronbach's alpha scores for the five measurement scales used in the study.

Table 2
Pilot study results

Construct	Cronbach's Alpha
ED	0.836
IN	0.872
OB	0.865
PC	0.795
RA	0.756
TE	0.823
TR	0.801

4.6 Survey Structure

The questionnaire survey was structured into the following sections and distributed to a sample of students (Sim et al., 2014):

- Personal Information: This section collected participants' personal details relevant to the survey.

- Behavioral Intention to Use AI: The second section included two items focused on participants' intention to use AI.

- Factors Influencing AI Adoption: The third section contained 15 items categorized under "Ease of Doing Business," "Observability," "Perceived Compatibility," "Relative Advantage," "Technology Export," and "Trialability." Responses were measured on a five-point Likert scale ranging from strongly disagree (1) to strongly agree (5), designed to accurately capture participants' views on the 17 items.

4.7 Data Analysis

To evaluate the research models relying on several classifiers, including OneR, BayesNet, J48, and Logistics, this research instead employs Weka (ver. 3.8.3). For determining the association in the research model, previous publications employed ML algorithms using various approaches including neural networks, Bayesian networks (Leong et al., 2013). Additionally, in contrast to other studies that used one stage of SEM analysis, the hybrid SEM-ANN technique is used in this study to verify the research hypotheses. Two phases make up the hybrid SEM-ANN model. PLS-SEM (Leong et al., 2013) is used in the initial stages to evaluate the research model. The conceptual framework is preliminary, so there is no pertinent research, thus the strategy is appropriate (Khan et al., 2018). PLS-SEM is also used in research to apply generic IS principles. Two methods were used for evaluating the research models: structural model analysis and measurement model analysis (Huang & Stokes, 2016). The Importance Performance Map Analysis (IPMA) provided by SmartPLS is used in the current research to evaluate the effectiveness and significance of every factor in the research model. An enhanced PLS-SEM methodology is IPMA. The PLS-SEM assessment is being verified with deep ANN in the subsequent stage.

Considering a non-linear and complicated input and output connection, deep ANN is an appropriate analytical method. The effectiveness of the predictor and predicted factors in the research model is also evaluated by employing the deep ANN. Three crucial approaches, learning rule, transmission function, and network architecture are typically used in ANN methods (Huang & Stokes, 2016). These three interprets are additionally separated into radian basis, recurrent network, and multilayer perceptron (MLP) networks. A popular approach, the MLP, binds output and input layers together through hidden nodes (Huang & Stokes, 2016) Predictors (neurons) in the input layer transport data to the hidden layers (Wang et al., 2017). The synaptic weights are used to transfer the data. Every output of a hidden layer is determined by the chosen activation function (Wang et al., 2017). The sigmoidal function is among the most often utilized activation functions. So, to evaluate the theoretical framework in this research, a neural network of MLP is used. Table 3 represents the convergent validity analysis.

Table 3
Convergent validity results which assure acceptable values (Factor loading, Cronbach's Alpha, composite reliability ≥ 0.70 & AVE > 0.5)

Constructs	Items	Factor Loading	Cronbach's Alpha	CR	AVE
ED	ED1	0.745	0.810	0.825	0.736
	ED2	0.860			
	ED3	0.745			
IN	IN1	0.760	0.897	0.871	0.724
	IN2	0.845			
OB	OB1	0.808	0.820	0.839	0.794
	OB2	0.912			
	OB3	0.745			
PC	PC1	0.855	0.817	0.819	0.641
	PC2	0.898			
	PC3	0.813			
RA	RA1	0.745	0.812	0.820	0.656
	RA2	0.770			
	RA3	0.745			
TE	TE1	0.713	0.857	0.829	0.644
	TE2	0.845			
	TE3	0.728			
TR	TR1	0.841	0.854	0.836	0.785
	TR2	0.805			
	TR3	0.860			

Table 4
Fornell-Larcker Scale

	ED	IN	OB	PC	RA	TE	TR
ED	**0.802**						
IN	0.465	**0.817**					
OB	0.493	0.646	**0.877**				
PC	0.272	0.469	0.261	**0.851**			
RA	0.243	0.396	0.267	0.419	**0.847**		
TE	0.259	0.551	0.405	0.406	0.522	**0.826**	
TR	0.251	0.489	0.360	0.388	0.519	0.401	**0.759**

Table 5
Heterotrait-Monotrait Ratio (HTMT)

	ED	IN	OB	PC	RA	TE	TR
ED							
IN	0.660						
OB	0.245	0.328					
PC	0.708	0.172	0.439				
RA	0.345	0.577	0.457	0.390			
TE	0.224	0.398	0.283	0.342	0.354		
TR	0.198	0.127	0.257	0.330	0.268	0.333	

4.8 Hypotheses testing using PLS-SEM

Every path's variability representation (R^2 value) and connection's path significance in this study model were assessed. Fig. 3 and Table 7 point out the normalized path coefficients and path significance. The overall testing of the nine above mentioned hypotheses was done utilizing the structural equation modeling (SEM) method (Sandu & Gide, 2019). These constructs consequently seem to possess moderate predictive power (Sandu & Gide, 2019). The empirical data corroborated hypothesis H1, H2, H3, H4, H5, H6, H7, H8, H9, and H10 according to the data analysis. According to Table 6, the R2 values for technology export, ease of doing, and adoption of AI applications ranged from 0.546 to 0.631.

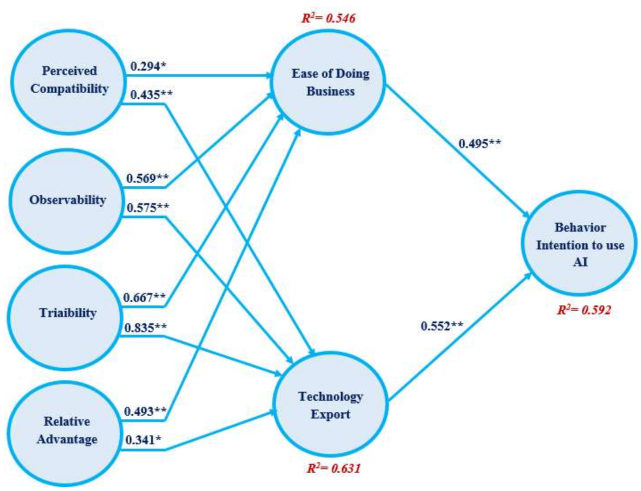

Fig. 3. Path coefficient of the model (significant at p** < = 0.01, p* < 0.05).

The study findings indicate that four key factors, namely Perceived Compatibility (PC), Observability (OB), Trialability (TR), and Relative Advantage (RA), have significant effects on both Ease of Doing Business (ED) and Technology Export (TE). Specifically, the results demonstrate that PC, OB, TR, and RA have positive effects on ED (β= 0.294, P<0.05), (β= 0.569, P<0.01), (β= 0.667, P<0.01), and (β= 0.493, P<0.001) respectively, thereby supporting hypotheses H1, H3, H5, and H7. Similarly, the results show that PC, OB, TR, and RA have significant effects on TE (β= 0.435, P<0.001), (β= 0.575, P<0.001), (β= 0.835, P<0.001), and (β= 0.341, P<0.05) respectively, thereby supporting hypotheses H2, H4, H6, and H8.

Furthermore, the study findings reveal that the relationships between ED and TE have a significant impact on the Behavior Intention to use AI (IN). Specifically, the positive effects of ED and TE on IN were found to be significant (β= 0.495, P<0.01) and (β= 0.552, P<0.001) respectively, thereby supporting hypotheses H9 and H10.

Overall, the results of this study suggest that the factors of PC, OB, TR, and RA have a significant impact on both ED and TE, which in turn have a significant influence on the intention to use AI.

Table 6
R^2 of the endogenous latent variables.

Construct	R^2	Results
ED	0.546	Moderate
IN	0.592	Moderate
TE	0.631	Moderate

Table 7
Hypotheses-testing of the research model

H	Relationship	Path	*t*-value	*p*-value	Direction	Decision
H1	PC → ED	0.294	5.368	0.029	Positive	Supported*
H2	PC → TE	0.435	15.798	0.000	Positive	Supported**
H3	OB → ED	0.569	14.744	0.001	Positive	Supported**
H4	OB → TE	0.575	16.884	0.000	Positive	Supported**
H5	TR → ED	0.667	14.339	0.003	Positive	Supported**
H6	TR → TE	0.835	17.971	0.000	Positive	Supported**
H7	RA → ED	0.493	19.145	0.000	Positive	Supported**
H8	RA → TE	0.341	3.242	0.032	Positive	Supported*
H9	ED → IN	0.495	13.025	0.002	Positive	Supported**
H10	TE → IN	0.552	18.350	0.000	Positive	Supported**

4.9 Hypotheses testing using classical machine learning algorithms

The research's first, third, fifth, and seventh hypotheses are all corroborated by these findings. The Bayesian network, neural network, and decision tree were only a few of the techniques used with the ML algorithm for evaluating the research's hypotheses. These methods were applied to the conceptual framework to predict the connection (Sandu & Gide, 2019). The prediction has been verified using Weka (ver. 3.8.3), which relies on classifiers like J48, OneR, and BayesNet (Sandu & Gide, 2019). J48 showed the best performance in evaluating ED, according to Fig. 4. Since it projected ED with an accuracy of 82.38% for ten-fold cross-validation, it provided the best performance. The most enhanced performance was again provided by J48, as evidenced by its 81.27% precision, 81.38% recall, and 82.24% F-Measure.

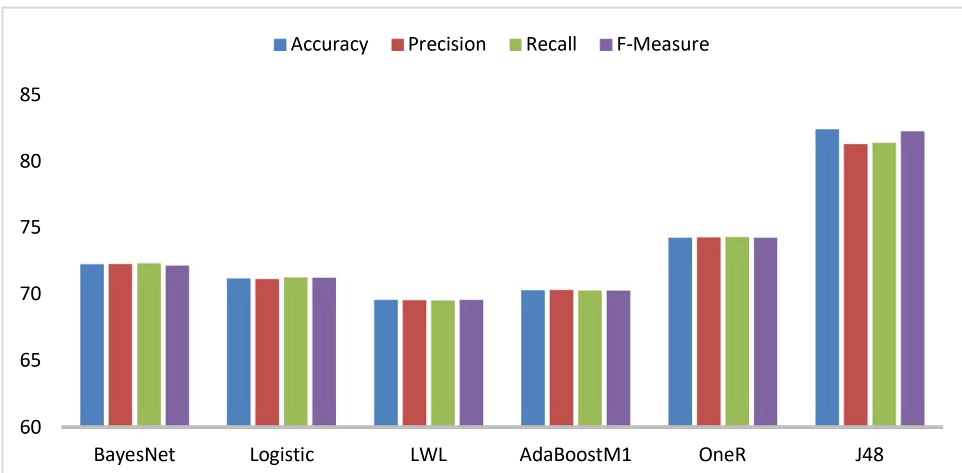

Fig. 4. Impact of PC, OB, TR, & RA on ED

The findings so concur with the second, fourth, and sixth hypotheses of the research. The best performance in predicting TE was likewise recorded by J48. It accurately predicted TE 78.68% of the time (refer to Fig. 5).

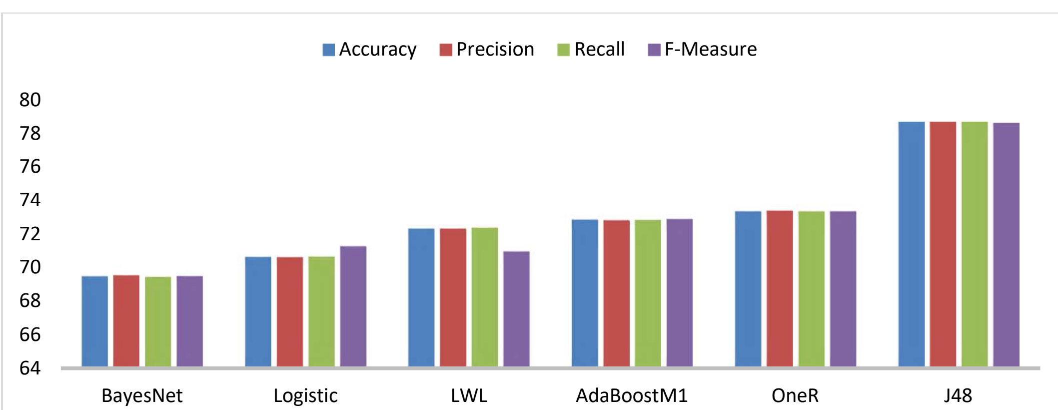

Fig. 5. Impact of PC, OB, TR, & RA on TE.

J48 also showed the most enhanced performance in predicting IN utilizing ED and TE features. It is accurately estimated IN 86.32% of the time (refer to Fig. 6). The ninth and tenth hypotheses were therefore also confirmed.

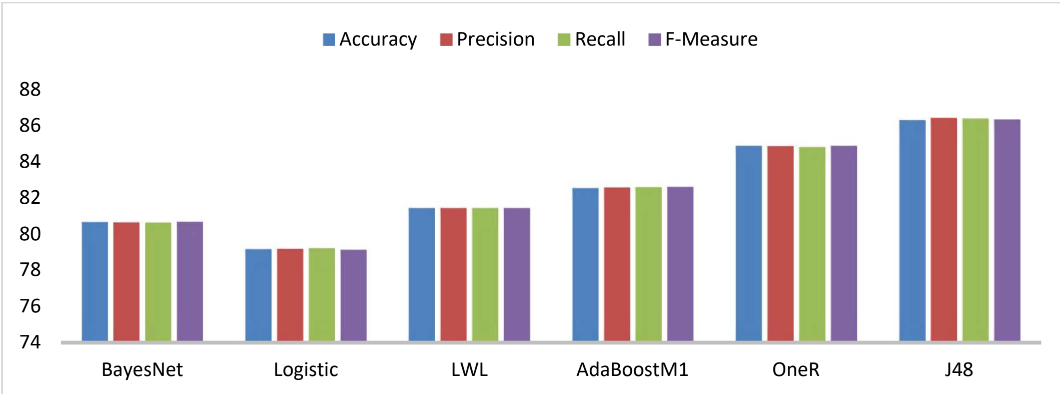

Fig. 6. Impact of ED & TE on IN

4.10 Sensitivity Analysis

The intention to use AI is the most important predictor of behavior, as seen in Table 8. The second and third foremost predictors of behavior intention to use AI are the PEOU and PCO, respectively. To determine the normalized importance, the mean for every independent is compared to the mean percentage with the largest number. The performance and accuracy of deep ANN analysis have been verified employing the goodness of fit (comparable to R-squared in PLS-SEM) (Wang et al., 2017). The outcome demonstrates that compared to PLS-SEM (R^2= 59.2%) and ML algorithm (R^2= 86.32%), deep ANN revealed higher prediction power (R^2= 94.7%). The outcome demonstrates that deep ANN is superior to PLS-SEM and ML algorithms in describing endogenous constructs. But when it comes to predicting non-linear relationships between constructs, deep learning outperforms PLS-SEM and ML algorithms.

Table 8
Independent Variable Importance.

	Importance	Normalized Importance
PC	.223	68.3%
OB	.317	87.0%
TR	.266	73.0%
RA	.441	78.9%
ED	.051	14.1%
TE	.559	100.0%

4.11 Importance-Performance Map Analysis

Since IPMA improves the interpretation of PLS-SEM testing, it is significant (Wang et al., 2017). The primary factor in the current research, which uses IPMA, is behavioral intention. IPMA analyses performance measures alongside assessing importance measures or path coefficients. The overall impact within IPMA demonstrates how behavioral intentions (target factors) are influenced by importance measures, and how well they perform is indicated by the mean of the latent construct. According to IPMA, Figure 7 illustrates the importance and performance of ED, IN, OB, PC, RA, TE, and TR. TE indicated the utmost importance and performance numbers, next to OB, according to Figure 10. RA got the least performance measure score and the third-highest importance measure score. The least important measure score was provided by ED.

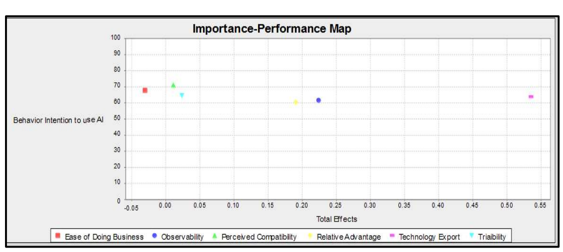

Fig.7. IPMA Output.

5. Discussion of Results

The current research primary objective was to evaluate the way artificial intelligence (AI) applications are used in pedagogical contexts. To make that possible, two major factors were pinpointed: ease of doing business and technology export play a vital role in determining and affecting the adoption of AI applications. The diffusion theory, which has many independent variables, helps establish a model for adoption, and specifies how much these variables affect AI adoption. Findings of this study show that the ease of doing business (ED) and the export of technology (TE) have a clear influence on adoption. To evaluate the hypotheses, this research also employed a hybrid methodology that combined PLS-SEM, ML, and deep ANN. The outcome demonstrated that deep ANN promotes IN quite significantly. Compared to the ML algorithm and PLS-SEM, the ANN model demonstrated a higher power for prediction. A substantial link between ED and TE was also discovered by the research. The results demonstrate that participants' views on AI were influenced by both human and technology-based characteristics. AI adoption increases with increased ED and TE.

Using ED helps specify which context suits enhancing innovations. The most recent results are incompatible with prior research, for this study indicates that ED can positively affect the adoption of technology. Through ED, the willingness of individuals to adopt innovation is significantly increased. With the use of this special evaluation, organizations can highlight how well they can face significant business challenges. If companies are prepared to utilize technology, they thrive. Recognizing the process of doing business as simple points out to the fact that individuals can swiftly adopt novel technologies. This study concentrated on the technological exports consisting of commodities and solutions demanding substantial development time and financing. Technology innovation includes electrical devices, hardware as well as technological assistance and innovation. The impact of each of these factors on AI adoption in connection to technology export is significant.

The statistical analysis produced findings highlighting the significant relationships among the different conceptual model variables. Observability, perceived compatibility, trialability, and relative advantage are the other three variables which could be associated with the first three mentioned above.

The first is that "observability, perceived compatibility, trialability, relative advantage" and ease of doing business enjoy a noteworthy relationship. Governments are capable of working effectively anytime its demands are answered with technology with no additional challenges, (Nawaz et al., 2024). Hence, relative advantage consciousness, accessibility, user-friendliness, service quality, network dependability benefit, and ease are all connected to adopting technology. Perceived value and the relative advantage of an innovation are significantly related (Nawaz et al., 2024). People's perception of their need for innovations transcends their recognition of how important the current practices are. The diffusion of innovation theory points out that innovation will propagate rapidly depending on its perceived relative advantage.

Compatibility was the main factor influencing technology (Strauss et al., 2024). Results show that compatibility and AI have a strong relationship. According to a research paper (Strauss et al., 2024), incompatible inventions are less adopted than the compatible ones, which highlight the fact that they demand an element of force to get past obstacles and seize chances. Hence, compatibility may be utilized as an independent variable to predict the level of adoption in governmental context, working as an alarm system for its considerable importance (Chatterjee and Bhattacharjee, 2020).

5.1 Theoretical and Practical implications

Since it is a rare type of research that applies ML algorithms for predicting AI, the hybrid approach used in the current paper adds to the body of IS research. Based on a conceptual standpoint, the PLS-SEM and ML algorithms employed in this study were utilized for verifying the research model. PLS-SEM can predict dependent variables and evaluate the conceptual model, according to the study (Sandu & Gide, 2019). Corresponding to this, Arpaci (2018) shows that ML can predict dependent variables from predictor variables. This research is distinctive since it combined different methods with ML algorithms. Decision trees, Bayesian networks, and neural networks were some of these approaches. The J48 or decision tree, nevertheless performed superior to the other techniques. J48 was employed to categorical and continuous values as a non-parametric approach. After reducing the sample into comparable smaller samples according to relevant predictors, the classification was carried out (Sandu & Gide, 2019). The non-parametric PLS-SEM approach was utilized to evaluate the significance of the coefficients. Compared to the ML algorithm and PLS-SEM models, the ANN model demonstrated higher predictive power. The deep architecture of ANN, helping to specify non-linear correlations among variables, is a contributing factor to its higher predictive power.

Users' faith and readiness can be significantly affected by both the ease of doing business and the export of technology. The progress that can be gained in providing solutions at an educational institution has practical implications. The application of AI is improved by these two factors. Compatibility has a favorable relationship with the intention to adopt AI. The adoption rate for AI could be raised if the developers of these apps can be persuaded to include additional compatible specifications. Hence, app programmers and developers have to consider incorporating extra resources and methods to interact with consumers, plus recommending elements different from the conventional resources employed by all educational institutions. Similarly, a better level of adoption intention has been generated as a result of the favorable correlation between trainability and relative advantage, which altered how individuals previously thought of pedagogical institutions and assisted in creating a more advanced and easy-to-access system. A framework can be built through the process of offering transparent information regarding the enactment process via public websites. To prepare for a system that is more inventive in the future, these devices are employed as learning methods.

5.2 Managerial Implications

AI is viewed as a cutting-edge technology which has the ability to better people's well-being as well as enhance individual growth. According to the research's findings, the management implications can benefit the education sector by enabling more innovative AI adoption. The findings highlighted that innovation and progress are vital elements of education. The top brass should push for AI adoption in their educational institutions. Up-to-date studies may assist managers and developers with difficulties arising from employing AI. The recommended elements which help increase the awareness of the importance of AI in the pedagogical context are to be modified by apps developers.

5.3 Limitations of the Study and Future Studies

This current study has a lot of limitations. The primary limitation is that the research model is limited to a group of factors that are utilized as measuring and focusing the effect of AI. Prospective research may include additional factors that support the desired outcomes people have been focusing on, like the examination of factors affecting AI adoption intentions. Moreover, claiming that the findings can be generalized is not an easy feat, since they are restricted to a specific country. Additional studies in other contexts are much needed in order for this study's findings to be corroborated so as to obtain a better view in this field. Lastly, this study has highlighted the DOI theory's applicability to AI within administrations in underdeveloped countries. Future studies may utilize different factors to produce similar results.

6. Conclusion

AI adoption brings into attention how innovative technology will be utilized in different governmental contexts, which can bring about major advantages from enhanced efficiency. The research concluded that observability, compatibility, trialability, and relative advantage are all connected to an effective metric in the DOI theory. They have an impact on how AI is adopted in educational institutions. According to the research's findings, compatibility significantly influences the ease of doing business and exporting technologies. Individuals adopting AI applications consider innovation to be compatible with how they live, which explains its significant influence. If AI meets the demands of the governing bodies' intentions, people will gain a lot from the innovation of technology. Hence, people can effortlessly alter and substitute a current product or concept. Additionally, the research found that trialability, vital for promoting adoption, has a huge effect on AI adoption. As per the findings, people want to explore and try out AI before making a final decision. Government agencies will be inclined to adopt AI, resulting in providing people with state-of-the-art functions which can offer services to the pedagogical institutions and pave the way for potential development. To improve such potential growth and for better future plans, this current study recommends the adoption of AI applications across different government institutions.

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