Jilin Daxue Xuebao (Gongxueban)/Journal of Jilin University (Engineering and Technology Edition)
ISSN: 1671-5497
E-Publication: Online Open Access
Vol: 42 Issue: 10-2023
DOI: 10.5281/zenodo.10012067

ANTICIPATING THE INTEGRATION OF ARTIFICIAL INTELLIGENCE IN HIGHER EDUCATION: EXPLORING ADOPTION MODELS AND PREDICTING ITS FUTURE IN MOROCCAN UNIVERSITIES

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Abstract

Purpose: The emergence of artificial intelligence (AI) in many fields has shown how modern technological advances are being introduced y into the educational process of higher education institutions. In the current context, some educational institutions have exploited AI to interact with students and optimize their learning by tracking their progress (Wang, & al., 2018; Yang, 2022; Kaklauskas, 2015). This article defines artificial intelligence as an educational technology and studies this process to anticipate the future nature of the higher education system in the world, where AI becomes a part of the structure of not only higher education, but society as a whole. The objective of this study is to predict how teachers might adopt it in Moroccan universities. To do this, we drew on many adoption models and theories, including the extended Unified Theory of Acceptance and Use of Technology (UTAUT2), To explain professor's attitudes and behavioral intent toward the use of artificial intelligence in higher education Design/methodology/approach – A survey was conducted among Moroccan higher education professors to assess attitudes and behavioral intention towards the use of artificial intelligence in the education process. The questionnaire was administered online only and 98 responses were received in a 40-day period, from March 3, 2022 to April 9, 2022, using Google Forms as a medium. We adopted the structural equation modeling technique based on partial least squares (PLS-SEM) to analyze the relationship between the latent variables: perceived risk, performance expectancy, effort expectancy, facilitating conditions, behavioral intention. To this end, SmartPLS 3.0 software was used to create path diagrams and calculate the significance of factor loadings using the bootstrap technique. Findings – The main results indicate that effort expectancy and performance expectancy have a positive impact on attitude. And attitude with facilitating conditions have a positive impact on behavioral intention towards the use of artificial intelligence by higher education teachers in Morocco. Overall, the model, proved to be a better model to explain the antecedents of attitude and intention of use. In addition to the risk has no effect on the attitude towards the use of artificial intelligence by university professors. Originality/value – To the best of our knowledge, this is the first attempt of its kind to assess the role of perceived risk in examining the antecedents of attitude toward the adoption of artificial intelligence within a UTAUT model. This study examined the antecedents of attitude and behavioral intention to use artificial intelligence applications by higher education professors in the Moroccan context.

Keywords: Artificial Intelligence, Attitude, Behavioral Intention, UTAUT2, Morocco.

1. INTRODUCTION

The use of information and communication technologies for education has revolutionized the concepts of interactivity, connection, linking, and empowerment of information (Akhmedov, 2022). The irrefutable advancement of technologies in the digital field has reshaped the plans of human activity, is accelerating changes in social perspective significantly, and will continue to forge a high impact on the sciences with increasingly

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precipitous trends (Camargo, Lima, & Torini, 2019). Since the beginning of the 21st century, there has been the integration of emerging technologies in the educational environment (Fandos, 2009), which has allowed the increase of information and communication technologies (ICT) in learning environments, and this is precisely where open educational resources and learning objects express their best educational potential (Mezarina et al., 2015; Colomé, 2019).

The future of higher education is inextricably linked with the development of new technologies and the computing, the computing power of new intelligent machines. In the educational segment, the introduction and application of artificial intelligence opens up new opportunities and forms new challenges for teaching and learning in higher education institutions, with the potential to fundamentally change in management and significant changes in the internal architecture of higher education institutions. Artificial Intelligence (AI) is the ability of machines to use algorithms, learn from data and use what they learn to make decisions just as a human being does (Celik, 2023). AI has marked a before and after in the history of computing, in the technological evolution and especially during crises, it has led people to develop academic-scientific research only with the use of the Internet and social networks (Rezapour, M., & Elmshaeuser, S. K. 2022).

In Morocco, higher education has undergone an evolution to prepare young people for the academic-work scenarios that will occur in the future due to the digital transformation related to the fourth industrial revolution (Ouajdouni & al., 2021; Tamer & knidiri, 2023). This revolution is characterized by the intelligent interconnection of various digital technologies such as 3D printing, artificial intelligence or the internet of things to achieve a more efficient production system (Chávez & al., 2023). Thus, the paradigm of Education 4.0 emerges, which promotes self-learning through reflection in a training context supported by technology and its use to work on educational content and would aim to avoid inequalities in social development (UNCTAD, 2019).

With the integration of emerging technologies in higher education, new perspectives of teaching strategies are beginning to emerge, which are now accommodated and manifested in their virtual format (Almaiah, & al., 2022). It is in this context that the topic is explored further. The following questions remain:

How might AI applications impact the higher education system in Morocco?

What are the antecedents that influence the attitude towards AI adoption and what is their impact on the intention of AI adoption by higher education professors in Morocco?

The purpose of this article is to study professors’ attitudes towards AI adoption. It is based on the above questions and projects the general horizon of knowledge in this area.

2. LITERATURE REVIEW

Within the framework of a scientific and technological revolution driven by information and communication technologies (ICT), whose impact has transformed the world and given rise to the Information Society 5.0, artificial intelligence (AI) and its accelerated evolution have emerged as a protagonist due to its strong potential in solving complex problems

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(Bali, Kumalasani, & Yunilasari, 2022). Its massive presence constitutes an unprecedented computing paradigm that has contributed significantly to improving the quality of life of human beings, solving social problems and, more than tackling uncertain future scenarios, building desired ones (Khan, & Khojah, 2022). The revolution is not over, the new challenge is the integration of the digital world into the physical world with the human being as the central axis and the intelligent systems at the service of people living together in the new 5.0 society, fairer for all (Haderer, & Ciolacu, 2022; Carayannis, & Morawska-Jancelewicz, 2022).

AI should be understood as a scientific discipline that shapes machines to be intelligent and capable of solving problems by anticipating the action of the environment through adaptability and learning, and capable of solving problems by anticipating the action of the environment through their ability to adapt and learn patterns (Tuomi, 2018; Hooshyar & al., 2020; Ma & al., 2015). In the current context, some educational institutions have leveraged AI in the form of chatbots or virtual tutors to interact with students and optimise their learning by tracking their progress, assessing assignments or providing instant assistance (Wang, & al., 2021; Salas-Pilco, & Yang, 2022; Kaklauskas,& al., 2018). Another branch of AI used in the field of education is machine learning, understood as an AI system that builds mathematical models, based on data recorded as a sample, to make predictions or decisions, mimicking human intelligence. emulate human intelligence without having to program it first (Jin & al., 2020 ; Naqa & Murphy, 2015; Sekeroglu, & al., 2019), argue that machine learning is effective when used in education and can be used to predict student performance and plan courses. In addition, it can be used to update teaching models according to the evolution of the learner, as well as to update content and educational activities (Sánchez-Vila, & Penín, 2007). In this line, Artificial intelligence is a technology whose market value is incalculable in developing countries and especially for developing countries, both in the present and in the future, but we should not refer only to the monetary value, we should also analyze the value it has for the optimization of non-commercial processes, as in the Moroccan education sector : AI is and will be a turning point in the changes of traditional educational paradigms, although the pedagogical modalities at all levels of educational systems are being adapted, given the current technological tools, virtual education modalities are becoming more common in the educational policies of first world countries. AI can optimize the use of these valuable resources, as one of the main problems today is the underutilization of technological tools or their isolated and out of context use.

Sometimes technological advances do not fulfil the desired expectations. There are several possible explanations for this, including the factors that lead to adoption and use. ICT adoption is an evolutionary process that requires certain minimum thresholds of technological infrastructure to reach greater maturity (Mallick, 2021; Papastergiou, 2021). Understanding the motivations and drivers of ICT adoption has been a goal of researchers and business people (Chow, 1967; Taylor and Todd, 1995a ; Taylor and Todd, 1995b). Therefore, given all the benefits that artificial intelligence offers to higher education, it would be prudent to determine whether it would be adopted by professors.

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This research will use the Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh, & al. It has been applied and validated in many fields. Originally developed in the field of organisational business, it has been validated in academic fields (Huang, 2013). It has also been validated with different technologies (Altalhi, 2021), including artificial intelligence (Chatterjee, & Bhattacharjee, 2020). This model was chosen because it is one of the most current, the one that best explains the adoption of a system, reaching levels of predictability above 70%, and because it is one of the most complete, integrating the most important constructs of the previous eight theories. Throughout the different studies, it has proven to be a good predictor of both the intention to use and the use of information systems.

3. CONCEPTUAL FRAMEWORK AND HYPOTHESES

The UTAUT model integrates eight theories (TRA, TPB, TAM, MM, C-TAM-TPB, IDT, MPCU, SCT) of individual acceptance into one model. It helps to understand which factors facilitate or hinder the adoption of artificial intelligence. The importance of the model lies in its ability to understand the process of AI adoption. The importance of the model lies in understanding the process of technology acceptance and the factors involved, in order to maximise the factors that contribute to determining the adoption of the technology. There are a number of models for measuring technology adoption. These do not provide a universal approach to predicting user behaviour and acceptance of information and communication technology (ICT) based systems. Venkatesh et al (2003) conducted a detailed analysis of eight models of technology acceptance and use in order to find one that could overcome the limitations of existing models by bringing together the common concepts of each model and formulating the Unified Theory of Technology Acceptance and Use.

This study aims to validate Venkatesh, (2003) UTAUT model on Moroccan higher education. The original model postulates that performance expectancy, effort expectancy and social influence affect intention to use, while facilitating conditions determine behavioural intention and adoption of artificial intelligence. It further postulates that gender, age, experience and voluntariness are involved in this process, therefore, in our reflection, we dropped the moderating variables. Therefore, we have removed the social influence variable because it is not an imposition or pressure factor to be used by bosses or superiors, but rather it is understood that in the context of public universities, teachers have enough freedom to integrate or not certain pedagogical innovations.

We included a new construct, "perceived risk", as an important exogenous variable, as was done in another study (Chatterjee, & Bhattacharjee, 2020, AlHadid, & al., 2022). We believe we were able to justify the choice of these constructs such as perceived risk (PR), performance expectancy (PE), effort expectancy (EE), facilitating condition (FC), and behavioural intention.

Perceived Risk

This variable refers to the nature and level of risk that an individual perceives when considering a specific decision. In the age of information technology, perceived risk is

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considered by several studies to be a decisive predictor in the adoption of information and communication technologies (Kim, Mirusmonov & Lee, 2010; Savas, 2017) due to the significant impact it can have on users' attitudes in their use of artificial intelligence in higher education (Tat et al., 2020 ; Nguyen, & Llosa, 023). Therefore, we have formulated the following hypothesis:

H1: Perceived risk (PR) has a positive impact on professors' attitudes (ATT) toward using artificial intelligence (AI) in higher education

Performance Expectancy (PE)

The construct of performance expectancy is based on five models:

TAM/TAM2/combination between TAM and TPB; MM; MPCU; IDT and SCT. From the compilation of these, Venkatesh, & al. (2003, p.447) defined performance expectancy as the degree to which the individual believes that by using the system, he or she will gain job performance. In other words, performance expectancy is the subjective probability that the user of the technology has regarding its performance, in relation to the fact that the use of this technology will improve its performance compared to previous technologies (Davis, 1989; Davis, & al., 1989; Venkatesh & al.,2003). Based on this empirical research, we assume that:

H2: Performance expectancy (PF) has a positive impact on professors' attitudes (ATT) toward using artificial intelligence (AI) in higher education

Effort Expectancy (EE)

The effort expectancy was developed on three models very similar in definitions and scale measures: TAM/TAM2; MPCU and IDT. Effort expectancy is related to the degree of effort, to the extent that the user of the technology considers that the use of the same will not cause him to develop greater effort (Davis, & al., 1989). In other words: "it refers to the user being free of effort when he/she intends to use the technologies (Davis, 1989 ; Davis, & al., 1989; Venkatesh, & al. 2012). Through it, the individual relates the degree of ease associated with using the system (Venkatesh &, al.,2003). We have therefore retained as hypothesis :

H3: Effort expectancy (EE) has a positive impact on professors' attitudes (ATT) toward using artificial intelligence (AI) in higher education

Facilitating conditions (FC)

The construct called facilitating conditions is described as the degree to which the individual believes that there is an organizational and technical infrastructure to support the use of the system (venkatesh, & al., 2003, p.453). According to the authors, this definition concentrates concepts embodied by three different constructs: perceived control of behavior (TPB/DTPB, TAM/TPB combination), facilitating conditions (MPCU) and compatibility (IDT).

H4a: Facilitating Conditions (FC) has a positive impact on professors' behavioral intention (BI) to use artificial intelligence (AI) in higher education.

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H4b: Facilitating conditions (FC) have a positive impact on the effort expectancy (EE) for using artificial intelligence (AI) in higher education.

Attitude (A) and the Behavioral Intention (BI)

Attitude is the general disposition that an individual develops in relation to a behavior. It reflects the individual's feelings of approval or disapproval toward the performance of the behavior (Ajzen, 1991; Fishbein and Ajzen, 2000). An attitude is defined as "a psychological tendency that is expressed by evaluating a particular entity with some degree of approval or disapproval" (Van Birgelen, de Ruyter and Wetzels, 2003). Ajzen (1989) describes attitude as a "predisposition of individuals to respond favorably or unfavorably to a specific object" (p. 241); however, it should be noted that this factor does not predispose an individual to engage in a particular behavior, but rather leads to a set of intentions to perform a certain action (Ajzen & Fishbein, 1975). Intentions are indicators of the effort that individuals are willing to exert in order to develop the behavior (Ajzen, 1991), so they capture factors of motivation to use group buying websites. In turn, they are the main determinant of individual behavior (Ajzen, 1991; Davis, & al., 1989) so it is a useful construct to explain the acceptance behavior of collective purchasing websites. TAM traditionally argues that there is a significant correlation between attitudes toward a particular technology and its actual use by individuals (Davis, 1986); this assumption is supported by several studies in the educational field (Chuang, & al., 2016; Hu, & al., 2019; M. Lee, 2011 ; Marakarkandy, & al., 2017; Zhang, & al., 2018), which have shown that attitude has a highly positive and significant effect on the intention to adopt artificial intelligence . Therefore, the above led to the establishment of the following study hypothesis:

H5: Attitude (ATT) have a positive impact on professors' behavioral intention to use artificial intelligence (AI) in higher education.

4. DATA AND METHODS

A survey was conducted to assess the intention behind the use of artificial intelligence by higher education professors in Morocco. The questionnaire was administered online only and 98 responses were received using Google Forms as a medium. The sampling technique used was convenience sampling due to the ease of access to email addresses and the higher response rate.

The study adopted the partial least squares-based structural equation modeling (PLS-SEM) technique proposed by Hair et al. (2011) to analyze the relationship between the latent variables (Perceived Risk (PR); Performance Expectancy (PE); Effort Expectancy (EE); Attitudes (ATT); Facilitating Conditions (FC); and Behavioral Intention (BI)).

The analysis was performed in two phases, the relationship between the latent constructs and the indicators was tested, and in the structural model, the relationship between the latent constructs was tested by the PLS method. SmartPLS 3.0 software was used for this purpose.

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As proposed by Henseler and Sarstedt (2013), the first phase included the evaluation of the measurement model, through the analysis of the reliability of the indicators, convergent validity, and discriminant validity.

The reliability of the internal consistency of the constructs was checked by calculating the composite reliability as proposed by Chin, (1998) and its value must be greater than 0.7. The average variance extracted (AVE) was used to analyze convergent validity to examine the unidimensionality of the constructs, with AVE required to be greater than 0.5 (Fornell & Larcker, 1981). Discriminant validity was examined by calculating the cross-loadings used by Henseler and Sarstedt, (2013) to test whether the square roots of the AVEs were greater than the correlations between constructs.

The second phase of the evaluation consisted of evaluating the structural model by applying the bootstrap technique using the SmartPLS software. The values of the path coefficients (β) and the value (p) were used to evaluate the nature, intensity and significance of the hypothesized relationships between the constructs.

Next, the R of the model in which the relationships between the antecedents and the dependent variables (behavioral intention and attitude) were analyzed to assess the explained variability of the (perceived risk, facilitating conditions, ease, and utility)

The R^2 value is between 0 and 1, and the value closest to 1 indicates a greater proportion of variability explained by the selected antecedents, Cohen (1988) suggests that R^2 values for endogenous latent variables be evaluated as follows: 0.26 (substantial), 0.13 (moderate), 0.02 (low).

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In addition, the significance of the path coefficients for analyzing the relationship between the latent concepts was also examined using the bootstrap method in SEM-PLS. SEM-PLS allows for the calculation of path coefficients as well as their significance level for all relationships in the structural model.

5. ANALYSIS RESULTS

The objective of the research is to identify the antecedents of behavioral intention and adoption of artificial intelligence applications by higher education professors in Morocco.

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5.1. La Fiabilité des Indicateurs

To accept measurement instruments, the factor loadings of the different factors belonging to a construct must be above the 0.70 threshold value and reported as significant (Ringle et al., 2019).

Although this model has an explanatory power of 53% for behavioral intention, careful observation revealed indicators with factor loadings (PR5 = -0.632 and BI4 = 0.685) as low at the 0.70 standard (table below). In order to meet the construct validity criterion, the indicators PR5 a and BI4 were removed to achieve better model fit and construct validity.

The models shown in the path diagram in the figure above are the models before and after deleting the observed variables PR5 and BI4 ;

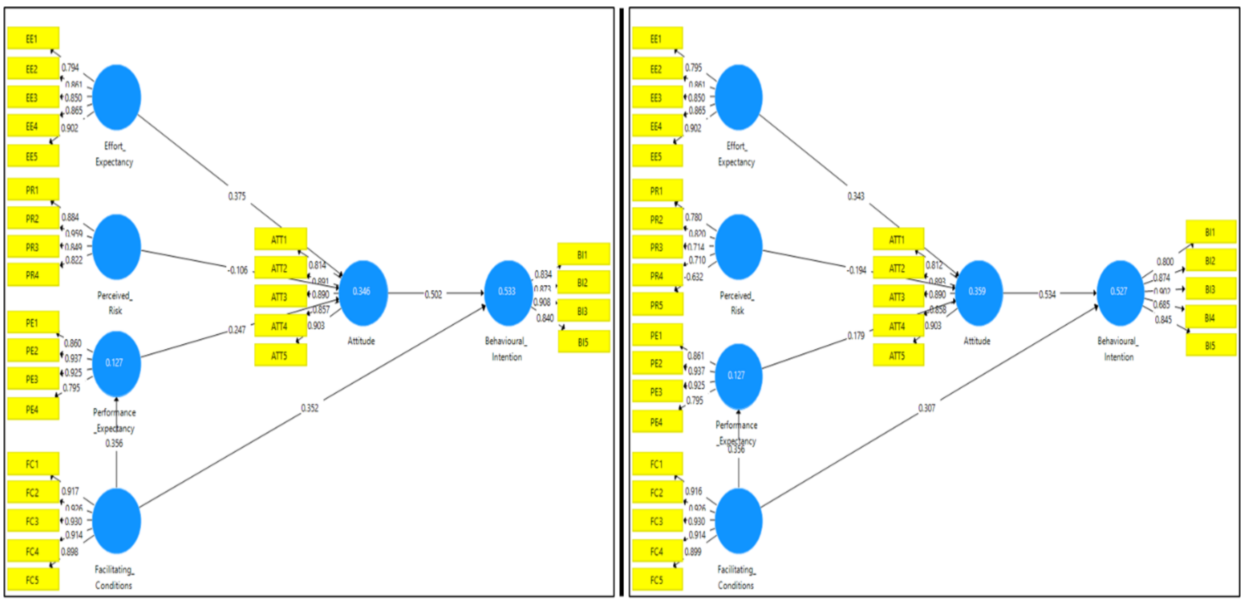

Figure 1: the measurement model before and after the removal of Indicators PR5 and BI4

Table 1: Reliability of Indicators

	Item	Factor Loading
Attitude	ATT1	0.813
	ATT2	0.892
	ATT3	0.891
	ATT4	0.855
	ATT5	0.903
Behavioural-Intention	BI1	0.799
	BI2	0.874
	BI3	0.903
	BI4	**0.684**
	BI5	0.847
Effort Expectancy	EE1	0.795
	EE2	0.861
	EE3	0.850

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	EE4	0.865
	EE5	0.902
Facilitating Conditions	FC1	0.916
	FC2	0.926
	FC3	0.930
	FC4	0.914
	FC5	0.899
Performance Expectancy	PE1	0.865
	PE2	0.939
	PE3	0.921
	PE4	0.793
Perceived Risk	PR1	0.781
	PR2	0.821
	PR3	0.714
	PR4	0.711
	PR5	**-0.632**

5.2. La validité convergente et la validité discriminante

The table below provides a comparative overview of the most important statistics for construct reliability and validity as well as discriminant validity. Construct reliability and validity was measured using Cronbach's Alpha, composite reliability, and AVE, and all are greater than 0.6. Discriminant validity was assessed by examining the Fornell-Larcker criterion.

According to the results presented in the table below, the Cronbach's Alpha value of all constructs is greater than 0.70, showing that the reliability of the measurement indicators (Nunnaly et al., 1967). In addition, the composite reliability is above the desirable value of .60 in all cases (Bagozzi, 1988). The average variance extracted (AVE), shown in the table below is above the threshold for all constructs, therefore, the conditions for reliability and convergent validity have been met by the measurement model.

We can see that the value of the mean variance of a construct shown diagonally in the table below that it is greater than the corresponding correlation coefficients shown outside the diagonal. This confirms the test of discriminant validity (Fornell and Larcker 1981).

Table 2 : Convergent and Discriminant Validity

	ATT	BI	EE	FC	PR	PE	Cronbach's α	Rho_A	Composite reliability	AVE
ATT	**0.871***						**0.921**	**0.925**	**0.940**	**0.760**
BI	0.660	**0.865***					**0.887**	**0.891**	**0.922**	**0,748**
EE	0.533	0.589	**0.855***				**0.908**	**0.919**	**0.931**	**0.731**
FC	0.450	0.576	0.584	**0.917***			**0.953**	**0.958**	**0.964**	**0.841**
PR	-0.272	-0.247	-0.255	-0.224	**0.880***		**0.909**	**0.992**	**0.932**	**0.774**
PE	0.474	0.425	0.529	0.356	-0.279	**0.881***	**0.903**	**0.911**	**0.933**	**0.777**

5.3. Hypothesis Testing Using Partial Least Squares Structural Equation Modeling

Once we obtained a satisfactory measurement model, we tested the structural model that includes the hypothesized relationships between the constructs perceived risk, performance expectancy, effort expectancy, facilitating conditions, attitude, and

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behavioral intention of professors to use artificial intelligence (AI) in higher education (PR, PF, EE, FC, ATT and BI). The structural model was estimated by applying the bootstrap technique, which is a resampling technique that draws many subsamples, such as 500, from the original data (Vinzi et al., 2010). The standardized path coefficients in the table below indicate the estimates and significance of the hypothesized relationships between the constructs.The first hypothesis H1 examines the impact of perceived risk (PR) on professors' attitudes (ATT) toward the use of artificial intelligence (AI) by higher education professors in the Moroccan context. The analysis shows that the perceived risk (PR) does not have a significant impact on faculty attitudes towards the use of AI in higher education. Indeed, the path coefficient involved is also low (β = -0.106) with a significance level (p = 0.392 ns).

Furthermore, the second hypothesis H2 examines the impact of performance expectancy (PE) on professors' attitudes (ATT) toward the use of artificial intelligence (AI). The results of the analysis show that performance expectancy does indeed have a positive and significant impact on faculty attitudes toward the use of AI with a path coefficient of (β = 0.247) with a significance level (p = 0.016).The third hypothesis H3 examines the impact of effort expectancy (EE) on faculty attitudes (ATT) toward the use of artificial intelligence (AI). At the end of the analysis, it appears that effort expectancy has a positive and significant impact on professors' attitudes towards the use of AI in higher education. This is with a positive path coefficient of (β = 0.375) and significance level (p = 0.000).

The fourth hypothesis H4 is divided into two sub hypotheses. On the one hand, H4a which analyzes the impact of facilitating conditions (FC) on the effort expectancy (EE) of the use of artificial intelligence (AI) by higher education teachers in Morocco. According to the table below this hypothesis was effectively accepted with a positive path coefficient of (β = 0.356) and significance level (p = 0.000). On the other hand, H4b which analyzes the impact of facilitating conditions (FC) on the behavioral intention (BI) of higher education professors towards the use of artificial intelligence (AI). From this analysis, it is found that facilitating conditions have a positive impact on behavioral intention to use AI with a positive path coefficient of (β = 0.352) and significance level (p = 0.000).

Finally, Hypothesis H5 which investigates the impact of attitude (ATT) on higher education professors' behavioral intention (BI) towards the use of artificial intelligence (AI). The results of this analysis show that attitude has a positive impact on behavioral intention with a positive and significant path coefficient of (β = 0.502) and significance level (p = 0.000).

Table 3: Test of Research Hypotheses

Hypothèses		**Échantillon initial (β)**	**Valeur-P**	**Remarque**
H1	PR -> ATT	-0.106	0.340	Rejetée
H2	PE-> ATT	0.247	0.016	Acceptée
H3	EE-> ATT	0.375	0.000	Acceptée
H4b	FC-> PE	0.356	0.000	Acceptée
H4a	FC -> BI	0.352	0.000	Acceptée
H5	ATT-> BI	0.502	0.000	Acceptée

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5.4. The Adequacy And Explanatory And Predictive Power Of The Structural Model

The model fit indices indicate that the model is a good fit in the table below, as the standardized mean root of the residual (SRMR), Chi-square, and the standardized fit index (NFI) are all sufficiently acceptable to validate the model fit.

Table 4: Summary of Structural Model Fit

	saturated model	estimated model
SRMR	0.082	0.129
D_ULS	2.519	6.267
D_G	1.605	1.708
Chi-squared	831.340	855.367
NFI	0.711	0.703

In addition, the table below shows that the analysis of the R^2 shows the model has an explanatory power for the attitude up to 34.6%, for the behavioral intention up to 53.3% and finally the performance expectancy is 12.7%. Moreover, the model shows a predictive relevance since all the values of Q^2 are higher than 0.

Table 5 : R^2 and Q^2

	R^2	**Q^2**
PE	0.127	0.070
ATT	0.346	0.227
BI	0.533	0.363

6. DISCUSSION AND IMPLICATIONS

The general objective of this study was to evaluate and analyze the perceptions of professors on the uses, potential and difficulties derived from the use of Artificial Intelligence in their teaching-learning process, starting from the creation of AI-based Open Educational Resources.

The great impact in the field of higher education has not only changed traditional teaching practices, but has also produced changes in the infrastructure of educational institutions, generating concepts such as smart campuses (Pandey and Verma, 2017; Sánchez-Torres et al., 2018) or smart universities (Rico-Bautista et al., 2019; Berenguer-Murcia, 2017). To analyze, propose and develop infrastructures in an organization, for example in universities, it is necessary to know the architectures and their technologies (Rico-Bautista et al., 2019).

The role of universities has changed due to the irruption of the technological revolution and globalization, which means the need to learn how to manage technologies to enhance their contribution to society. Artificial intelligence continues to emerge and make breakthroughs (Shaoyong et al., 2016) it is creating a sustainable and intelligent infrastructure. Artificial intelligence is a complex phenomenon, and understanding the technical, organizational, and human factors that contribute to its effective use is essential to providing organizations with a roadmap to improve the outcomes of their large projects (Surbakti et al., 2020). Several researches have generated results internationally, a

Jilin Daxue Xuebao (Gongxueban)/Journal of Jilin University (Engineering and Technology Edition)
ISSN: 1671-5497
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DOI: 10.5281/zenodo.10012067

literature review from 1990 to 2017, 97% of the literature focuses on the internet of things and AI (specifically, 55% of the literature focuses on AI and 42% of the studies focus on the internet of things), was conducted by Rjab and Mellouli, (2018), the authors showed the importance given to the integration of artificial intelligence in higher education.

AI has created many opportunities for higher education. AI has become a key competitive asset and a central part of the decision-making process of various industries (Kumar, 2019). For the model proposed by this research, UTAUT (Venkatesh, 2003), has been taken as the basis, which raises four fundamental aspects: performance expectancy, effort expectancy, social influence, and facilitating conditions. The UTAUT has been successfully tested in different contexts for almost 20 years. In this study, an adaptation of the UTAUT is proposed as a research model to measure attitude toward behavioral intention to use AI by higher education professors. One of the conclusions of the study proposing the UTAUT model (Venkatesh et al., 2003) is that the social influence variable is only relevant in environments where the use of technology is mandatory and only becomes significant in environments where the use of ICT is free, it should be clarified that it is not an imposing or pressuring factor to be used by bosses or supervisors, but rather it is understood that in the context of public universities, teachers have sufficient freedom to incorporate or not some pedagogical innovations. On this basis and given the freedom to use scientific databases, the social influence variable was removed.

The general objective of the study is based on this question, which aims to analyze the factors that influence the intention of AI use by higher education professors in the Moroccan context.

At the same time, the results of our study, highlighted the influence that performance expectancy, effort expectancy exert a positive influence on the attitude towards the intention to use AI technologies. These results are consistent with those of several studies of artificial intelligence adoption that have used the UTAUT or TAM (Bere, 2014, Qi et al., 2012, Chatterjee et al., 2020; Ragheb et al., 2022; Raffaghelli et al., 2022; Crompton and Burke, 2023). This shows that professors would be inclined to adopt AI if they perceive a tangible benefit. In other words, if the technology allows them to perform their tasks faster, more efficiently, autonomously, and with mobility, allow them to achieve their goals more quickly, and increase their performance. Also, let us point out that the influence of the variable effort expectancy has shown that the perception of the attitude towards the use of artificial intelligence by higher education professors will be without difficulty or extra effort (Davis, 1989; Venkatesh, 2003).

The results underline that the impact of facilitating conditions is strong. This does not seem surprising insofar as it is considered by both the TAM and the UTAUT as well as by the different empirical studies as the variable most significantly related to the intention to adopt AI. These results relate to the availability of material, temporal, technical, and financial resources needed to support professors' engagement in AI adoption behavior. The results are better when the institution is more committed, it is not just about being ahead of the curve with this tool, if not contributing to its proper use to increase good outcomes; a good attitude towards the learning process, the use and adoption of new technologies such as AI can make a difference.

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The variable the perceived risk does not have an influence on the attitude towards the use of AI by higher education professors. The rejection of this variable is explained by the measures taken into account by the Moroccan state to guarantee information security. In higher education institutions, these measures are taken on a large scale to ensure the implementation of emerging technologies in universities. In the case of AI in particular, and based on previous experiences with the integration of information and communication technologies in higher education, professors have a clear understanding of the technology and find no risk from their uses in the educational process.

Research on professors' adoption of AI has demonstrated the importance for universities to align information technology with strategic goals, address risks, use resources to execute strategies, ensure value creation, and select and use metrics to evaluate change. From this perspective, the adoption of AI technologies is the result of strategic management deliberations that address implementation, risk issues (Medina-Cárdenas & Rico Bautista, 2016). The reason why we included perceived risk, as a latent variable explaining the attitude towards the use of AI.

Similarly, it is important to redefine the role of university professors and consider them not only as instructors, but also as coaches in the processes of creating resources and developing technological skills, as stated by Taveras et al. (2021).

However, as León and Viña (2017) and Eaton et al. (2018) point out, the integration of AI brings related challenges that educational institutions and professors must face. In this sense, university professors identify the need to incorporate AI into the educational process, and to study the technological resources available to higher education institutions in order to guarantee equitable access to artificial intelligence technology for professors but also for students, thus it is necessary to train teachers in the use of AI by providing pedagogical support through the creation of a national or international community of practice in a virtual environment accessible at any time and place.

7. LIMITATIONS AND FUTURE RESEARCH

The main limitations of our work are that the research was conducted over a specific period of time, which prevents us from considering the variation in individual beliefs over a longer period of time. Therefore, it would be desirable to conduct a longitudinal study to more clearly appreciate these changes, expanding the number of subjects to ensure greater external validity of the results. As we have seen above, another limitation is related to the study of complex systems. In our case, the process of adopting the combined methodology at the universities studied is still in its infancy. This means that many teachers do not know enough about what it really means to work in an environment where there is a real balance between face-to-face teaching and virtual teaching guided by artificial intelligence, which may result in many not being aware of the real potential of this type of methodology and even, if they intend to use it, of the precise moment when they should do so. In summary, there is a need to develop further studies with other samples of university teachers in our context in order to replicate and contrast the preliminary findings of this study. Given the limitations of the study, we would like to

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emphasize that the sample is small and that it would be desirable for this study to be replicated with students or administrators.

8. CONCLUSIONS

Artificial intelligence is a technology with a considerable market value, both in the present and in the future, but we must not only refer to the monetary value, we must analyze the value it has for the optimization of non-business processes, and especially in the higher education sector ; AI is and will be a turning point in the changes of traditional teaching paradigms, although the pedagogical modalities at all levels of educational systems are being adapted, given the current technological tools, virtual teaching modalities are becoming more common in the educational policies of the most developed countries.

AI can optimize the use of these valuable resources, as one of the main problems today is the under-use of technological tools or their isolated and out-of-context use. As the proposals put forward show, AI can be of great use in the higher education sector, as it will help to find alternative solutions to the major problems that educational systems are currently facing. The social and economic model, and in particular the knowledge and forms of communication and information, have advanced by leaps and bounds, and it is worrying that one of the most important sectors of society, the higher education sector, is becoming increasingly dependent on information and communication technologies.

Moreover, AI can be of great use in the Moroccan higher education sector, today Morocco has put in place several strategies with the aim of improving the quality of higher education and integrating innovative technologies, strategies that will allow the development of alternative solutions to the major problems that the education systems are currently facing. As the social and economic model, and in particular knowledge and forms of communication and information, have advanced by leaps and bounds, it is worrying that one of the most important sectors of society, the higher education sector, is reluctant to abandon its traditional educational paradigms, If it does not adapt to the new models and skills that society demands, especially the technology offered by AI, it will cease to be a pillar of society and simply become an obsolete sector of society with little influence on the social and economic dynamics of the future.

The use of AI to guide future students in universities is a necessary step, as the Moroccan state has invested significant amounts of its gross domestic product (GDP) in the university sector. This is an investment that the government makes in their citizens, who deserve not only to be guided when choosing a professional career, but also an adequate monitoring of their performance is necessary in order to detect the risk factors that can lead to the evolution of their students.

From a theoretical perspective, on the one hand, this research can serve as a starting point for further studies wishing to address the explanatory factors of behavioral intention of AI use in Morocco. On the other hand, the results of the study are consistent with previous work and (León and Viña, 2017; Eaton et al., 2018; Chatterjee et al., 2020; Ragheb et al., 2022; Raffaghelli et al., 2022; Crompton and Burke, 2023) make an important contribution to the validation of UTAUT.

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In terms of managerial implications, this study provides relevant information for scenario design of teacher acceptance of artificial intelligence in general and of innovative technologies in learning.

Finally, it seems clear that teachers are sensitive to adopt them sooner or later, if only to improve their professional image, due to perceived elements of the university environment that act as motivators (pressure from the academic management or from the students themselves) or simply by imitation effect (peer influence).

If the university wants to develop a platform or an application of artificial intelligence, it will have to take into consideration the performance expectancy and the effort expectancy of using these technologies. Also, the applications and functionalities offered should provide pedagogical activities based on institutional support for professors and foster a favorable institutional, infrastructural and financial environment (Kouakou, 2015). In addition, teachers should be sensitized to the importance and benefits of technology and artificial intelligence in accordance with the recommendations by UNESCO (UNESCO Strategy on Technological Innovation in Education, 2021-2025).

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