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Analyzing the adoption of artificial intelligence by Moroccan university teachers: Key insights and implications from the UTAUT model

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Abstract: This study examines the factors influencing the adoption of artificial intelligence (AI) by Moroccan university teachers, using the UTAUT model. A questionnaire was distributed to 75 professors at Sidi Mohamed Ben Abdellah University in Fez, and the data were analyzed using structural equation modeling (SEM). The results show that facilitating conditions and social influence are the primary determinants of AI adoption intention. In contrast, performance expectancy and effort expectancy had no significant impact. This research highlights the need to enhance technological infrastructure and implement targeted training programs to foster AI integration in Moroccan higher education. It contributes to the literature by extending the UTAUT model to an underexplored cultural and educational context while providing practical recommendations for overcoming barriers to AI adoption in developing countries.
Keywords: *AI Adoption, Artificial intelligence (AI), Digital transformation, Morocco, University teachers, UTAUT Model.*

1. Introduction

Artificial intelligence (AI) is revolutionizing various sectors, including education, offering unprecedented opportunities to improve teaching and learning [1]. According to Viberg, et al. [2] AI can personalize educational pathways, automate administrative tasks and provide advanced analytics to support pedagogical decisions. However, despite these potential benefits, the adoption of AI in higher education remains uneven, particularly in developing countries such as Alam [3]. In Morocco, the education system faces structural challenges, such as a lack of technological infrastructure, resistance to change and the need for ongoing teacher training [4]. Although the Moroccan government has launched initiatives to integrate digital technologies into education, AI adoption by university teachers remains limited and under-researched [2, 5]. This raises crucial questions: What factors influence Moroccan teachers' intention to adopt AI in their teaching practices? What obstacles hinder this adoption, and how can they be overcome? These questions highlight a gap in both empirical data and theoretical understanding of AI adoption in higher education within developing contexts.

Addressing this gap is critical, as the successful integration of AI could significantly improve the quality of teaching and learning, increase efficiency in administrative processes, and better prepare students for a digitally-driven workforce. Understanding the factors that either encourage or hinder AI adoption among educators is essential for designing effective implementation strategies. Moreover, exploring these dynamics in the context of a developing country like Morocco offers valuable insights that can inform broader international efforts to foster digital transformation in education. The main objectives of this research are:

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i. To identify the key factors influencing the intention to adopt AI among Moroccan university teachers, using the UTAUT model.
ii. To assess the relative impact of performance expectancy, effort expectancy, social influence, and facilitating conditions on the behavioral intention to use AI.
iii. To provide practical recommendations for policymakers, educational institutions, and stakeholders to promote the effective integration of AI into Moroccan higher education.

To answer these questions, this study draws on the UTAUT model, widely used to explore the adoption of emerging technologies [5]. The UTAUT model incorporates four key dimensions: performance expectancy, effort expectancy, social influence and enabling conditions.

These dimensions have been validated in various contexts, including education Tarhini, et al. [6] but their application to AI adoption in developing countries remains scarce. This research aims to fill this gap by examining the drivers of AI adoption by Moroccan university teachers. Using a quantitative approach based on a questionnaire administered to a sample of 105 professors, this study explores how the dimensions of the UTAUT model influence their intention to use AI. The results of this research offer valuable insights for policymakers, universities and practitioners, proposing strategies to accelerate the adoption of AI in Moroccan higher education. In sum, this study contributes to the existing literature in three main ways. Firstly, it extends the application of the UTAUT model to an understudied cultural and educational context. Secondly, it identifies the key factors influencing AI adoption in a developing country. Finally, it proposes practical recommendations for overcoming barriers to AI adoption, thus opening up new perspectives for the integration of emerging technologies into education systems.

2. Theoretical Framework

The introduction of artificial intelligence (AI) in higher education opens up new prospects for improving pedagogical and administrative practices. However, its adoption depends on a number of behavioral factors. The UTAUT model, proposed by Venkatesh, et al. [5] provides a sound theoretical framework for exploring these dynamics. This model is based on four main constructs - performance expectancy, effort expectancy, social influence and facilitating conditions - which directly influence behavioral intention and actual technology use. This framework has been widely used to analyze the adoption of educational technologies, particularly in similar contexts such as the use of ChatGPT or other AI tools in education [1, 2].

2.1. Performance Expectation

Performance expectancy measures the extent to which a user perceives that a technology will improve his or her performance [5]. In higher education, teachers perceive AI as a tool that can improve their teaching practices and student success. A recent study on the use of ChatGPT revealed that the perception of academic benefits, such as improved results and time optimization, is a key factor in adoptionTautz, et al. [7]. Barteit, et al. [8] has also shown that teachers are more likely to adopt digital tools when they perceive tangible benefits for their professional performance. Research on learning management systems also confirms that the perceived value of digital tools plays a central role in their adoption [6, 9]. When it comes to AI, teachers are motivated by the possibility of automating repetitive tasks and personalizing learning, reinforcing their behavioral intent [10].

H_1: Performance expectation has a positive effect on intention to adopt AI among university teachers.

2.2. Expectation of Effort

Expectation of effort refers to the perceived ease of use of a technology. An intuitive interface and adequate technical support are determining factors in the adoption of new technologies. A study on the use of mobile-based educational apps, such as LabSafety, showed that ease of use is a key predictor of adoption intention Al-Emran, et al. [11]. Liu [12] confirm that the perception of ease of use reduces behavioral barriers, particularly in the context of educational technology adoption. In the context of higher education, AI, as an emerging technology, needs to be designed to integrate easily with teachers' existing practices. This ease of use has also been identified as an important factor in the adoption of immersive virtual reality tools in education [13].

H_2: Expectation of effort has a positive effect on intention to adopt AI among university teachers.

2.3. Social Influence

Social influence reflects an individual's perception of the expectations of those around him or her regarding the use of a technology. In an academic context, this includes recommendations from colleagues, superiors or the institution. A study of Google Classroom use found that institutional support and peer recommendations significantly increased intention to adopt the technology [9]. This dynamic is particularly true for conversational AI tools, such as ChatGPT, where social influence plays a key role in the early stages of adoption [10].

H_3: Social influence has a positive effect on intention to adopt AI among university teachers.

2.4. Facilitating Conditions

Enabling conditions refer to the availability of the resources needed to use a technology effectively, including technical support, infrastructure and training. In higher education, institutional resources, such as reliable digital platforms and training programs, are essential to foster the use of Venkatesh, et al. [5] have shown that these elements directly influence the actual use of technology. A study of technological and pedagogical factors influencing the adoption of generative AI-assisted courses (GACA) found that institutional support boosts teachers' confidence in using these technologies [10]. Furthermore, research into the adoption of e-learning systems has shown that supportive infrastructure is a key factor in ensuring sustainable use [6, 11].

H_4: Facilitating conditions have a positive effect on the effective adoption of AI by university teachers.

The hypotheses presented above are synthesized in the following conceptual model, which illustrates the relationships between the four main constructs and their influence on behavioral intention and actual AI use. This model will serve as the basis for future empirical analyses.

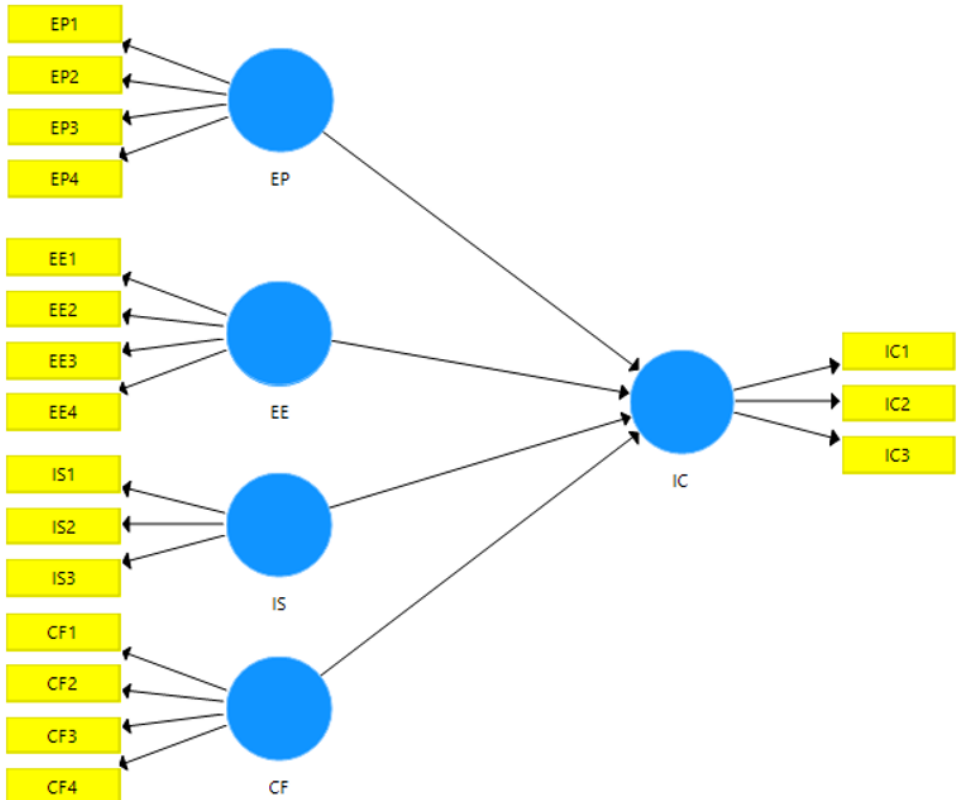

Figure 1.
Proposed conceptual modelConceptual framework for the effect of elements on intention to use.

3. Method

The research group consisted of university lecturers from Sidi Mohamed Ben Abdellah University in Fez, Morocco, as potential users of artificial intelligence (AI)-based technologies. Participants were selected from a variety of academic disciplines, including social sciences, exact sciences and medical disciplines, in order to obtain a representative sample of the university's faculty. Data were collected in December 2024 using an online questionnaire designed to assess perceptions and behavioral intentions towards AI, in line with the UTAUT (Unified Theory of Acceptance and Use of Technology) theoretical framework developed by Venkatesh, et al. [5]. The link to the questionnaire was shared via institutional channels such as internal mailing lists and WhatsApp groups used by teachers for academic purposes, to ensure relevant targeting. A total of 150 invitations were sent out, and 80 responses were collected. After a rigorous check to eliminate incomplete or inconsistent responses, 75 valid responses were retained for analysis. This verification process included an assessment of contradictory or repetitive responses, thus guaranteeing the quality of the data used in this study.

3.1. Measurements

The study variables, adapted from the UTAUT model, included performance expectations (PE), effort expectations (EE), social influence (SI), facilitating conditions (FC) and behavioral intention (BI). These variables are frequently used to assess the acceptance and use of technologies in various contexts [14]. Each variable was assessed using items validated by previous studies Dwivedi, et al. [10]; Wong [15] [10,17,18]; specifically adapted to the context of AI-based technologies. Participants' responses were collected on a five-point Likert scale, ranging from "strongly disagree" (1) to "strongly agree" (5).

3.2. Data Analysis

This study used SmartPLS 3 software and applied partial least squares structural equation (PLS-SEM) techniques, methods commonly used in management and the social sciences to explain the variance of dependent latent constructs [16]. The approach adopted is in line with the recommendations of Henseler, et al. [17]. For the calculation of beta values, reliability and standard error, it is necessary for the latent variables to have saturations greater than 0.7. A sample size of 75 participants is considered sufficient for PLS estimation methods. The validity of the PLS evaluation framework was verified by convergent and divergent validity analysis [17]. Finally, structural model and hypothesis analysis involved assessing path coefficients and determining the percentage of variance explained by antecedent variables, as suggested by Henseler, et al. [17].

4. Results

SmartPLS 3 software was used to evaluate the PLS-SEM modeling method for the proposed model [15]. With regard to sample size and residual distribution, the PLS method imposes minimal constraints [5]. In general, this approach avoids inadmissible solutions and factor indeterminacy when analyzing complex relationships between different variables [18]. In recent years, this method has been widely adopted in many business studies [10, 15, 17, 18].

4.1. Measurement Model

4.1.1. Examination of Reliability and Convergent Validity

The results of the analysis reveal that factor loadings are all above 0.5, attesting to good convergent validity [16]. The reliability of the model was assessed using several indicators. Firstly, Cronbach's alpha (α) for each construct is above 0.6, which is considered acceptable in exploratory studies [19]. Next, the composite reliability (CR) exceeds the recommended threshold of 0.7 for all variables, confirming the reliability of the items [16]. Finally, the average variance extracted (AVE) is greater than 0.5, validating construct convergence [19]. Discriminant validity was confirmed by the heterotrait-monotrait ratio, which remained below the critical threshold of 0.85 [17]. This indicates that the constructs are sufficiently distinct from each other. In addition, factor loadings above 0.7 demonstrate good item representativeness [20]. Finally, the assessment of reliability, measured by Cronbach's alpha and rho_A, revealed values above 0.7, indicating strong internal consistency [17].

Table 1.
Factor loadings, reliability, and convergent validity

Variable	Indic	L.f	Cro.Alpha	rho_A	CR	AEV
Performance Expectancy	PE1	0.818	0.852	0.862	0.900	0.693
	PE2	0.891				
	PE3	0.751				
	PE4	0.865				
Effort Expectancy	EE1	0.901	0.929	0.933	0.949	0.824
	EE2	0.920				
	EE3	0.904				
	EE4	0.906				
Social Influence	SI1	0.829	0.891	0.914	0.932	0.822
	SI2	0.942				
	SI3	0.944				
Facilitating Conditions	FC1	0.739	0.809	0.860	0.868	0.625
	FC2	0.827				
	FC3	0.706				
	FC4	0.878				
Behavioral Intention	BI1	0.922	0.802	0.935	0.874	0.706
	BI2	0.612				
	BI3	0.945				

4.2. Structural Model

4.2.1. Discriminant Analysis of Variables

The discriminant validity of a model evaluates the ability of a concept to distinguish itself from others. The matrices commonly used for this evaluation are the Fornell-Larcker criterion and the cross-loading matrix.

4.2.2. Fornell-Larcker Criterion

The Fornell-Larcker approach to validity assessment uses a matrix to examine the relationships between the different components of the model. For a construct to be considered valid in a discriminative context, the AVE root (mean of the extracted variance) of that dimension is assumed to have higher values than the connections with the other factors [19]. Table 2 shows that each construct meets this criterion. For Intention to Use (ITU), the square root of AVE is 0.840, which exceeds the correlations with the other constructs. For effort expectancy (EE), the square root of AVE is 0.908, which is also higher than its correlations with the other concepts. For facilitating conditions (FC), the square root of AVE is 0.790, although its correlation with PE (Performance Expectancy) is fairly close (0.719) and remains acceptable. For performance expectancy (PE), the square root of the AVE is 0.833, which is well above the correlations with the other concepts. For social influence (SI), the square root of AVE is 0.907, which is well above the correlations with the other concepts. These results, illustrated in Table 2, confirm that the constructs measure distinct concepts and possess satisfactory discriminant validity according to the Fornell-Larcker criterion, thus ensuring the robustness and reliability of our measurement model.

Table 2.
Fornell-Larcker Criterion correlation matrix.

	BI	EE	FC	PE	SI
BI	0.840				
EE	0.367	0.908			
FC	0.631	0.644	0.790		
PE	0.509	0.570	0.719	0.833	
SI	0.484	0.364	0.475	0.581	0.907

4.2.3. Cross-Loading Matrix

The cross-loading matrix is used to assess discriminant validity by comparing the coefficient values of each item on its associated construct with those of the other constructs. The table above shows that each item has a higher coefficient for its construct than for the other constructs. These results show that each item correctly assesses the construct with which it is associated, thus confirming the discriminant validity of all the constructs examined.

Table 3.
Matrix of crossover loads.

	BI	EE	FC	PE	SI
BI1	0.922	0.274	0.623	0.532	0.540
BI2	0.612	0.355	0.279	0.219	0.059
BI3	0.945	0.375	0.587	0.442	0.434
EE1	0.347	0.901	0.671	0.451	0.372
EE2	0.301	0.920	0.632	0.484	0.318
EE3	0.362	0.904	0.527	0.581	0.290
EE4	0.314	0.906	0.508	0.550	0.342
FC1	0.337	0.579	0.739	0.292	0.282
FC2	0.283	0.616	0.827	0.519	0.265
FC3	0.521	0.392	0.706	0.769	0.449
FC4	0.662	0.525	0.878	0.579	0.417
PE1	0.428	0.293	0.566	0.818	0.467
PE2	0.372	0.526	0.582	0.891	0.446
PE3	0.379	0.587	0.551	0.751	0.381
PE4	0.494	0.508	0.676	0.865	0.606
SI1	0.360	0.197	0.492	0.599	0.829
SI2	0.458	0.260	0.333	0.465	0.942
SI3	0.486	0.499	0.484	0.539	0.944

The results indicate that each item has a higher factor load on its construct than on the others, thus verifying the factor structure of the model.

4.2.4. Principle of Collinearity

Variance inflation factor (VIF) scores are used to examine interactions between explanatory variables in a predictive model. A VIF score below 5 is generally considered to indicate low collinearity between concepts. Table 4 shows the internal VIF values for the concepts analyzed. The results show that there is no significant correlation between the concepts studied, as the internal VIF values are all below the critical limit of 5. This confirms the robustness and reliability of the measures used in the model. These results are illustrated in the table of internal VIF values.

Table 4.
Internal VIF values.

	BI	EE	FC	PE	SI
BI					
EE	1.780				
FC	2.505				
PE	2.531				
SI	1.526				

4.3. Hypothesis Testing Results

The aim of testing the proposed hypothesis is to examine the direct causal relationships between the elements influencing intention to adopt AI. The results of the tests of hypotheses H1, H2 and H3 are described below.

Table 5.
Hypothesis testing results.

Hyp	Path	β (O)	M	SD	T	P	Conf.
H1	EE ➔ BI	-0.094	-0.076	0.175	0.534	0.594	Reject
H2	FC ➔ BI	0.565	0.573	0.194	2.920	0.004	Accept
H3	PE ➔ BI	0.017	0.020	0.131	0.130	0.897	Reject
H4	SI ➔ BI	0.240	0.234	0.101	2.383	0.018	Accept

The results of the PLS-SEM analyses, presented in Table 5, reveal significant insights regarding the determinants of behavioral intention (BI) in the context of artificial intelligence (AI) adoption by Moroccan university professors.

Facilitating conditions (FC) exert a positive and statistically significant impact on behavioral intention ($\beta = 0.565$, $p = 0.004$). This result confirms that the availability of the necessary resources, technical support and infrastructure plays a crucial role in the intention to adopt AI. This result is consistent with the work of Venkatesh, et al. [5] who emphasize the importance of facilitating conditions in the adoption of emerging technologies.

Social influence (SI) also shows a positive and significant effect on behavioral intention ($\beta = 0.240$, $p = 0.018$). This indicates that peer recommendations, institutional support and perceived social norms favorably influence AI adoption. This result is in line with studies by Tarhini, et al. [6] who highlighted the key role of social influence in the adoption of educational technologies.

In contrast, effort expectancy (EE) shows no significant impact on behavioral intention ($\beta = -0.094$, $p = 0.594$). This result suggests that perceived ease of use is not a key determinant of adoption intention in this context. This result contrasts with some earlier studies Venkatesh, et al. [5] but could be explained by the fact that Moroccan university teachers perceive AI as a complex technology, irrespective of its ease of use.

Similarly, performance expectancy (PE) showed no significant effect on behavioral intention ($\beta = 0.017$, $p = 0.897$). This implies that perceived benefits of AI, such as improved pedagogical or administrative performance, do not significantly influence adoption intention. This result could be explained by a lack of awareness of the concrete benefits of AI, or a mistrust of its real impacts.

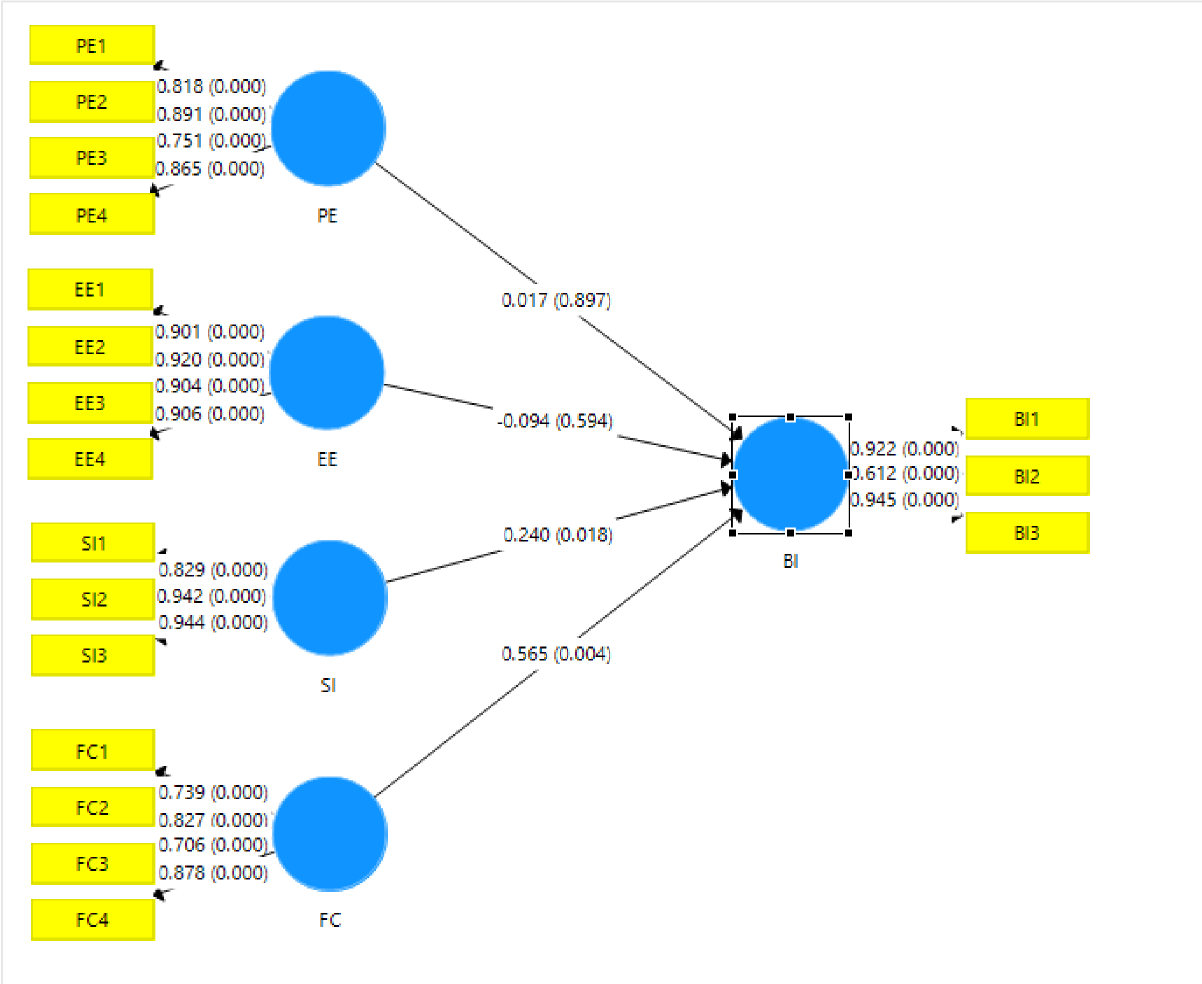

Figure 2.
Conceptual framework for the effect of elements on intention to use.

5. Discussion

The aim of this study was to explore the factors influencing Moroccan university teachers' intention to use AI, based on the UTAUT model. The results show that facilitating conditions (FC) and social influence (SI) are significant determinants of behavioral intention (BI), while effort expectancy (EE) and performance expectancy (PE) have no significant impact. These findings offer valuable insights for understanding AI adoption in a Moroccan educational context. Our results partly confirm those of Tarhini, et al. [6] who also found that facilitating conditions and social influence play a key role in the adoption of educational technologies. However, unlike our study, Tarhini, et al. [6] observed that performance expectancy was a strong predictor of intention to use. This discrepancy could be explained by contextual differences: in developed countries, the benefits of AI are often better understood and promoted, whereas in Morocco, teachers may lack awareness of the potential benefits of AI [1]. Similarly, our result on effort expectancy (EE) contrasts with that of Venkatesh, et al. [5] who showed that ease of use is a key factor in technology adoption. One possible explanation is that modern AI tools are increasingly intuitive, reducing the perceived importance of ease of use [2]. The lack of significant impact of performance expectancy (PE) on behavioral intention (BI) is surprising, as this dimension is generally a strong predictor in studies of technology adoption [5]. One possible explanation is that

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Moroccan teachers do not yet clearly perceive the benefits of AI for improving their pedagogical performance. This underlines the need for awareness-raising and training programs to highlight the concrete benefits of AI.

6. Conclusion

This study explored the factors influencing Moroccan university teachers' intention to adopt AI, using the Unified Theory of Acceptance and Use of Technology (UTAUT) model. The findings reveal that facilitating conditions such as access to adequate resources and infrastructure and social influence including peer support and institutional encouragement are key determinants of behavioral intention toward AI adoption. In contrast, performance expectancy (the perceived benefits of AI in enhancing performance) and effort expectancy (the perceived ease of use) did not show a significant impact. These outcomes underscore the predominant role of contextual and social elements in shaping technology adoption, particularly within the developing country context of Morocco. The study thus suggests that environmental and social enablers carry more weight than individual perceptions when it comes to integrating AI into educational practices.

This research extends the UTAUT model to a relatively underexplored context: the Moroccan higher education system. By focusing on a developing country with its specific challenges, it provides a deeper understanding of the factors that either encourage or inhibit AI adoption. The findings offer valuable guidance for universities and policymakers seeking to introduce AI technologies in education. To support the integration of AI in Moroccan universities, several actions are recommended:

- Strengthening Technological Infrastructure: A major obstacle to AI adoption remains the lack of adequate resources. Universities should invest in up-to-date hardware, software, and training facilities to facilitate AI integration.
- Fostering a Culture of Innovation: Encouraging collaboration and peer exchange can nurture a more innovative environment. Supporting initiatives that promote sharing experiences and best practices with AI can help embed it into academic culture.
- Raising Awareness of AI's Benefits: Many educators may not fully grasp AI's potential to enhance teaching. Awareness campaigns, workshops, and training can showcase practical applications such as automating tasks, personalizing learning, and supporting data-driven pedagogy.

Despite its contributions, the study has certain limitations. The sample was limited to Moroccan university professors, which may affect the generalizability of the findings to other educational systems or cultural contexts. Additionally, the cross-sectional design does not allow for assessing how intentions evolve over time. Future research could address these limitations by employing longitudinal methods, expanding to other educational levels, and including other relevant variables such as organizational culture, resistance to change, or digital literacy.

In conclusion, this study sheds light on the dynamics driving AI adoption in higher education and provides a foundation for evidence-based policy and institutional strategies. It contributes to shaping a more innovative, inclusive, and digitally empowered educational landscape in Morocco and serves as a reference point for similar transitions in other developing nations.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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