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Educational Technology Adoption in Moroccan Universities: Empowering Employability and Aligning with the Industrial Ecosystem

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ARTICLE INFO	ABSTRACT

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This study investigates the determinants of educational technology adoption among university faculty, with a particular emphasis on its contribution to the development of students' professional competencies in alignment with evolving industry expectations. Drawing on the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), data were collected from 80 faculty members at the Faculty of Legal, Economic and Social Sciences, Sidi Mohamed Ben Abdellah University of Fez, Morocco. Using structural equation modeling (SEM), the findings reveal that facilitating conditions are the only significant predictor of actual technology use. In contrast, perceived usefulness, perceived ease of use, and social influence show no statistically significant impact. These results underscore the importance of robust digital infrastructure and institutional support in enabling meaningful technology integration in higher education. The study provides actionable insights for policymakers aiming to bridge the gap between academic instruction and professional skill development through effective digital adoption.

Keywords: Educational technology; Digital adoption; Employability; Professional competencies; TAM; UTAUT; Morocco.

INTRODUCTION

In the era of rapid digital transformation, higher education institutions are under increasing pressure to align their pedagogical practices with the evolving demands of the labor market and the digital economy (OECD, 2022; Educ. Financ. Watch, 2022). Educational technologies have emerged as strategic tools to bridge the gap between academic instruction and the development of real-world professional competencies (Bond et al., 2020; Voogt & Roblin, 2012). By fostering interactive, learner-centered, and skills-based learning environments, these technologies contribute significantly to both academic excellence and student employability (Redecker, 2017; Ifenthaler & Yau, 2020).

Despite their potential, the successful integration of educational technologies largely depends on the willingness and capacity of university faculty to adopt and use them effectively (Selwyn, 2016; Alghamdi & Holland, 2020). The adoption process is inherently complex, influenced by a range of individual, organizational, and contextual factors particularly in Global South contexts, where technological infrastructure and institutional support may be inconsistent (Al-Adwan et al., 2018; Olasina, 2018).

Theoretical frameworks such as the Technology Acceptance Model (TAM) (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) have been widely applied to explain users' behavioral intentions in educational settings. These models highlight perceived usefulness, perceived ease of use, social influence, and facilitating conditions as key determinants of adoption. Recent studies have extended these models by integrating contextual and cultural dimensions, thereby confirming their relevance across diverse educational systems (Ain et al., 2016; Teo, 2011).

However, evidence suggests that the factors influencing technology adoption can vary significantly depending on institutional readiness, disciplinary cultures, and national policies (El-Masri & Tarhini, 2017; Uğur & Turan, 2018).

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In the Moroccan context, research on digital adoption in higher education remains scarce, particularly regarding how such technologies contribute to the development of students' professional skills (Kumar & Bervell, 2019; Briz-Ponce et al., 2017).

Given the increasing importance of employability and digital literacy in shaping students' futures, it is crucial to explore how universities, particularly in Morocco, can better integrate educational technologies to meet labor market needs. This study is therefore important because it addresses a double challenge: improving teaching effectiveness and enhancing students' professional preparedness in a context of rapid technological change.

The main research problem can be formulated as follows: **What are the key determinants that influence university faculty's adoption of educational technologies in Morocco, and how do these technologies contribute to enhancing students' professional competencies?**

Accordingly, the objectives of this study are threefold:

- **i.** To analyze the factors influencing faculty members' adoption of educational technologies;
- **ii.** To assess the role of these technologies in developing students' employability skills;
- **iii.** To provide recommendations for improving institutional strategies in higher education.

To achieve these goals, this paper is structured as follows: the introduction presents the context, importance, research problem, and objectives; Section 1 provides the literature review and theoretical framework; the methodology section describes the empirical design and data collection procedures; Section 3 presents the results and discusses the main findings and their implications; finally, the conclusion summarizes the key contributions, highlights the limitations, and offers suggestions for future research.

1.LITERATURE REVIEW AND THEORETICAL BACKGROUND

Educational technologies, continuously evolving, have played a major role in transforming pedagogical practices in higher education Zawacki-Richter et al., (2019). In response to the increasing demands of the labor market and changes in industrial ecosystems, it is imperative for academic institutions to rethink their pedagogical practices in order to develop students' professional competencies Redecker, (2017). In this context, the adoption of educational technologies by instructors plays a crucial role as a driver of this transformation. According to Alghamdi & Holland, (2020), effective integration of technology in pedagogical practices not only enhances student engagement but also fosters key competencies such as collaboration, critical thinking, and problem-solving. However, despite the perceived benefits, the adoption of educational technologies remains a complex process influenced by a multitude of individual, organizational, and social factors Scherer et al., (2019). The TAM, Davis, (1989) and its extensions, such as the UTAUT, Venkatesh et al., (2003), provide robust theoretical frameworks for understanding the underlying mechanisms of technology acceptance and usage. These models suggest that individuals' attitudes toward technology are primarily determined by variables such as perceived usefulness, perceived ease of use, social influence, and facilitating conditions. In the educational domain, several studies have confirmed the relevance of these models. For instance, Teo, (2011) demonstrated that perceived usefulness and perceived ease of use explain a significant portion of the variation in technology adoption by teachers. Ifenthaler & Schweinbenz, (2013) highlighted the role of facilitating conditions in the integration of tablet devices in educational settings. Social influence, in turn, has been recognized as a decisive factor, especially in environments where institutional culture values technological innovation Chao, (2019). Building on these works, our study aims to explore how these factors influence the adoption of educational technologies by higher education instructors, with the goal of better aligning pedagogical practices with the competencies expected in contemporary industrial environments. This analysis therefore lies at the intersection of two major dynamics: the digital transformation of higher education and the evolving demands of the labor market. Based on this theoretical framework, we will sequentially analyze the impact of each variable perceived usefulness, perceived ease of use, social influence, and facilitating conditions, on the actual use of educational technologies, drawing on the findings of prior research to support the formulation of our hypotheses.

1.1. Perceived Usefulness (PU)

Perceived usefulness refers to « *the degree to which a person believes that using a specific system will improve his or her job performance* » Davis, (1989). In higher education, it reflects teachers' belief that educational technologies help develop students' professional skills. Research consistently highlights its importance for technology adoption. Venkatesh & Davis (2000) identified perceived usefulness as a key predictor of effective information system use across professions. Teo (2011) showed that teachers who see technologies as beneficial for their teaching are more likely to integrate them. Briz-Ponce & García-Peñalvo (2015) emphasized the role of perceived usefulness in adopting mobile apps in medical education, while Mosunmola et al. (2018) confirmed its direct impact on mobile learning adoption in universities. More recently, Alghamdi & Holland (2020) demonstrated that the perceived usefulness of digital tools strongly shapes adoption in higher education. Ain et al. (2016) also found that students are more likely to engage with learning management systems when they perceive clear learning benefits. Based on these findings, we propose the following hypothesis:

H_1: Perceived Usefulness has a positive impact on the Actual Use of educational technologies to develop professional skills.

1.2. Perceived Ease of Use (PEOU)

Perceived ease of use is defined as « *the degree to which a person believes that using a system will be effortless*» Davis, (1989). In the university context, this means that teachers must perceive educational technologies as easy to handle in order to integrate them smoothly into their teaching. According to Davis (1989), perceived ease of use indirectly affects actual usage by influencing perceived usefulness.

Several studies have supported its importance: Briz-Ponce et al. (2017) showed that students are more likely to adopt mobile technologies for learning when they find them easy to use. Similarly, Mosunmola et al. (2018) confirmed that ease of use is a key factor in the adoption of mobile learning in higher education. Ain et al. (2016) demonstrated that in learning management systems, perceived ease of use directly influences students' intention to adopt the technology.

Al-Adwan et al. (2018) highlighted that the simplicity of mobile technologies plays a central role in their adoption in universities. Teo (2011) noted that even if its effect can be weaker than that of perceived usefulness, ease of use remains a significant factor in adoption decisions. Finally, Olasina (2019) showed that the intuitiveness and simplicity of learning platforms strongly shape students' willingness to engage in e-learning. Based on these findings, we propose the following hypothesis:

H_2: Perceived Ease of Use has a positive impact on the Actual Use of educational technologies to develop professional skills.

1.3. Social Influence (SI):

Social influence is defined as «*the degree to which an individual perceives that people important to him think he should use the new system*» (Venkatesh et al., 2003). In higher education, this refers to the influence exerted by colleagues, managers, or the academic environment encouraging technology integration into teaching.

Several studies have confirmed its central role in adoption. Briz-Ponce et al. (2017) showed that students' mobile learning behaviors are shaped by their academic environment. Similarly, Mosunmola et al. (2018) found that peer and teacher expectations significantly affect mobile learning adoption. Ain et al. (2016) emphasized the role of social perception in the use of learning management systems, underlining the influence of social norms. Alasmari and Zhang (2019), in the Saudi context, reported that social pressure and institutional climate positively affect mobile learning acceptance. Shen et al. (2019) further showed that reference group opinions influence the intention to adopt virtual reality in learning.

H_3: Social Influence has a positive impact on the Actual Use of educational technologies to develop professional skills.

1.4. Facilitating Conditions (FC)

Facilitating conditions refer to «*the extent to which an individual believes that an organizational and technical infrastructure exists to support system use*» Venkatesh et al., (2003). In universities, this includes access to digital resources, platforms, training, and technical support. Venkatesh et al. (2003) demonstrated that enabling conditions promote technology use. Al-Azawei et al. (2017) confirmed that technical support and appropriate resources drive e-learning adoption. Teo (2011) observed that novice teachers with proper equipment and support are more willing to use technology. Similarly, Briz-Ponce et al. (2017) noted that infrastructure and support tools boost mobile technology adoption in medical education. Al-Adwan et al. (2018) stressed the importance of logistical and technical support for educational technology uptake, especially in mobile learning. Mosunmola et al. (2018) also highlighted that access to resources and support is critical to mobile education adoption.

H_4: Facilitating Conditions have a positive impact on the Actual Use of educational technologies to develop professional skills.

In light of the literature review presented above, we propose a conceptual model to explain the adoption of educational technologies to develop vocational skills in higher education, in relation to the requirements of the industrial environment. The proposed model is based on four independent variables: Perceived Usefulness, Perceived Ease of Use, Social Influence, Facilitating Conditions and one main dependent variable: Actual Use of Educational Technologies. Each relationship proposed in this model has been supported by previous studies, as discussed. These relationships are formalized in the form of research hypotheses.

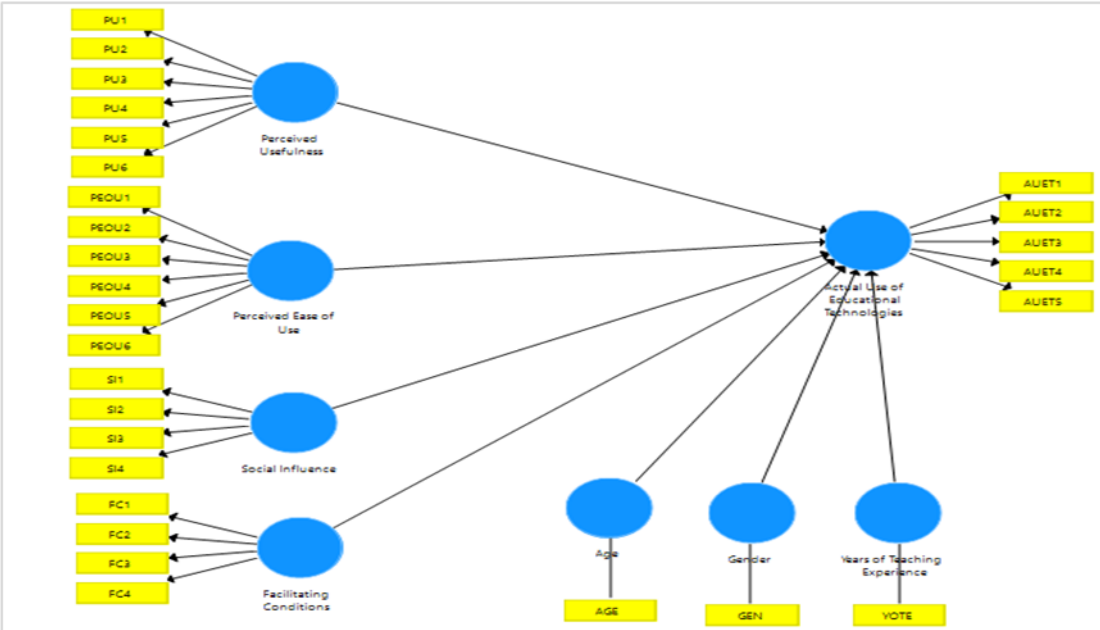

Figure 1: Proposed conceptual model.

2.METHODOLOGY

The research fieldwork focused on a targeted sample of faculty members affiliated with the Faculty of Legal, Economic and Social Sciences at Sidi Mohamed Ben Abdellah University, located in Fez, Morocco. This group was specifically selected due to its increasing familiarity with educational technologies and its representativeness within the management department, thereby ensuring disciplinary diversity in the analysis of digital practices in higher education. Data collection took place in February 2025 through a self-administered online questionnaire. This survey instrument was developed based on two prominent theoretical frameworks in the study of technology adoption: the Technology Acceptance Model (TAM), developed by Davis, (1989), which emphasizes the roles of perceived usefulness and perceived ease of use, and the Unified Theory of Acceptance and Use of Technology (UTAUT), proposed by Venkatesh et al., (2003), which introduces complementary dimensions such as social influence and facilitating conditions. The questionnaire link was disseminated through reliable institutional channels, including professional email accounts and dedicated WhatsApp groups used for communication among faculty members, in accordance with recommended dissemination practices in similar research contexts (Gomm, 2008). Out of the 200 faculty members invited to participate, 112 responded to the survey. Following a rigorous quality control process aimed at eliminating incomplete or inconsistent responses, 80 valid questionnaires were retained for statistical analysis. This data-cleaning phase is a crucial prerequisite for ensuring methodological rigor and the reliability of statistical inferences Hair et al., (2011).

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2.1. Measures

The study was structured around five key variables used to analyze the adoption of educational technologies in the university context: perceived usefulness (PU), perceived ease of use (PEOU), social influence (SI), facilitating conditions (FC), and actual use (AU). The conceptual constructs of perceived usefulness and perceived ease of use were operationalized based on the TAM developed by Davis, (1989), which remains a seminal framework for analyzing individual technology-related behaviors. The dimensions related to social influence and facilitating conditions were derived from the UTAUT, an integrative model proposed by (Venkatesh et al., 2003), which incorporates broader organizational and social determinants. The assessment of actual technology use was informed by recent studies on the integration of emerging technologies in higher education, particularly those of Chen & Zhou, (2016) , which offer empirically grounded indicators tailored to the digital educational context. All items were measured using a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"), allowing for a nuanced capture of respondents' perceptions and behaviors. To ensure content validity and contextual clarity of the questionnaire, a pre-test was conducted with a panel of ten faculty members, in accordance with established methodological best practices in the literature Dillman et al., (2016). This preliminary test enabled the refinement of certain formulations to improve clarity and relevance. Table 1 below presents a summary of the selected variables and their associated items, as structured according to the theoretical models employed.

Table 1. Summary of construct with measurement items

Construct	Corresponding Items
PU	**PU1**: The use of educational technologies in my teaching allows me to complete tasks more quickly.
	PU2: The use of educational technologies improves my professional performance, such as course management, communication with students, and assessment of their work.
	PU3: The use of educational technologies increases my productivity in teaching.
	PU4: The use of educational technologies enhances my efficiency in managing courses and students.
	PU5: The use of educational technologies facilitates the preparation and delivery of my courses.
	PU6: The use of educational technologies improves the quality of my teaching practices.
PEOU	**PEOU1**: It is easy for me to learn how to use educational technologies in my teaching.
	PEOU2: I find it easy to get educational technologies to do what I want them to do.
	PEOU3: It is easy to interact with educational technologies in a clear and understandable way.
	PEOU4: I find educational technologies flexible to use.
	PEOU5: It is easy for me to become skilled in using educational technologies in my teaching.
	PEOU6: I find educational technologies easy to use in my courses.
SI	**SI1**: People who influence my behavior think that I should use educational technologies in my teaching.
	SI2: People who are important to me (colleagues, mentors, etc.) believe I should use educational technologies in my teaching.
	SI3: The university administration has supported me in using educational technologies in my teaching.
	SI4: Overall, the university has supported the use of educational technologies in teaching.
FC	**FC1**: I have the necessary resources to use educational technologies in my teaching.
	FC2: I have the knowledge to use educational technologies in my teaching.

	FC3: I find that the educational technologies I use are compatible with other tools and systems in my work.
	FC4: There are people or groups available to help me solve technical problems related to educational technologies.
AUET	**AUET1**: I regularly use educational technologies to prepare my courses.
	AUET2: I integrate educational technologies into my classroom teaching.
	AUET3: I use educational technologies to interact with my students (e.g., course platforms, forums, messaging systems).
	AUET4: I use educational technologies for student assessment and monitoring.
	AUET5: I actively use technological tools to share teaching resources (e.g., slides, videos, interactive documents).

Source: Adapted from Davis (1989) for the TAM model and Venkatesh et al. (2003) for the UTAUT model.

2.2. Data analysis

The statistical analysis of the empirical data was conducted using SmartPLS version 3.3.9, employing the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach. This method is particularly recommended for exploring complex theoretical models and predicting causal relationships in emerging research contexts Hair et al., (2019). The measurement model was rigorously assessed through a validation process that included internal consistency reliability using Cronbach's alpha, composite reliability (CR), and convergent validity via Average Variance Extracted (AVE). Discriminant validity was verified based on the Fornell and Larcker criterion (Fornell & Larcker, 1981) to ensure conceptual distinction among constructs. Only factor loadings above 0.70 were retained, in accordance with established standards for indicator quality Hair et al., (2011). Regarding the structural model, path coefficients (β), t-values obtained via bootstrapping (5,000 resamples), and coefficients of determination (R^2) were analyzed to estimate the model's explanatory power. This methodological approach aligns with the guidelines proposed by Henseler et al., (2009) and Ketchen, (2013), who emphasize the relevance of PLS-SEM in applied social sciences. Moreover, the final sample size (n = 80) is considered adequate based on the "ten-times rule," which recommends a minimum of ten observations for each structural path directed toward a given construct in the model Hair et al., (2017).

2. EMPIRICAL RESULTS AND DISCUSSION:

The evaluation of the proposed structural model was carried out using SmartPLS 3, applying the PLS-SEM technique, which is particularly suited to exploratory research and theory development Hair et al., (2019). The PLS-SEM approach is known for its flexibility regarding sample size and distributional assumptions, making it an appropriate choice when data may deviate from normality or when dealing with complex models Hair et al., (2017). Moreover, this method is less prone to issues such as factor indeterminacy and inadmissible solutions, which are frequently encountered in covariance-based SEM approaches Henseler et al., (2015). Due to these advantages, PLS-SEM has become increasingly popular across a wide range of disciplines, including management, marketing, and information systems Alalwan et al., (2015).

2.1. Measurement model

To assess the adequacy of the measurement model, reliability and validity indicators were examined following the guidelines proposed by Hair et al., (2019). All item loadings exceeded the minimum acceptable threshold of 0.50, indicating acceptable convergent validity Hair et al., (2017). Internal consistency reliability was confirmed using multiple indices. Specifically, Cronbach's alpha (α) values for all latent constructs were above 0.70, which is generally deemed acceptable, even in exploratory research settings Nunnally et al., (1995). Moreover, CR values were all above the recommended cutoff of 0.70, suggesting high reliability among the constructs Fornell & Larcker, (1981). The AVE also exceeded the 0.50 benchmark for all constructs, confirming convergent validity. Discriminant validity was supported through the HTMT ratio of correlations, with all HTMT values falling below the conservative threshold of 0.85, as recommended by Henseler et al., (2015). This finding confirms that each construct represents a distinct conceptual entity. Additionally, most standardized loadings were above 0.70, reflecting strong item reliability Hair

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et al., (2019). Further assessments of reliability, including rho_A, yielded values above 0.70, reinforcing the internal consistency of the measurement model.

Table 2: Factor loadings, reliability, and convergent validity

Latent variable	IND	LF	α	rho_A	CR	AEV
AUET	AUET1	0.865	0.872	0.884	0.907	0.661
	AUET2	0.851				
	AUET3	0.833				
	AUET4	0.726				
	AUET5	0.783				
FC	FC1	0.853	0.784	0.811	0.859	0.605
	FC2	0.788				
	FC3	0.807				
	FC4	0.649				
PEOU	PEOU1	0.895	0.956	0.957	0.965	0.821
	PEOU2	0.934				
	PEOU3	0.891				
	PEOU4	0.88				
	PEOU5	0.914				
	PEOU6	0.92				
PU	PU1	0.916	0.957	0.967	0.966	0.825
	PU2	0.933				
	PU3	0.935				
	PU4	0.931				
	PU5	0.82				
	PU6	0.908				
Social Influence	SI1	0.717	0.789	0.806	0.863	0.612
	SI2	0.769				
	SI3	0.801				
	SI4	0.837				

Source: Authors' calculations based on SmartPLS 3 analysis results.

2.2. Structural model

Discriminant validity assesses the extent to which a construct is distinct from the other constructs in the model. It ensures that each concept measures a unique aspect of the phenomenon under study, without being confused with other constructs. Two common methods for assessing discriminant validity are the Fornell-Larcker criterion and the cross-loading matrix.

2.3. Critère de Fornell-Larcker

The Fornell-Larcker criterion involves comparing the square root of the AVE for each construct with its correlations with other constructs in the model. A construct is said to satisfy discriminant validity if the square root of its AVE exceeds its correlations with any other construct Fornell & Larcker, (1981). As shown in the analyzed table, all constructs meet this methodological requirement, thereby confirming the model's discriminant validity. The AUET demonstrates a square root of AVE of 0.813, which is greater than its correlations with other constructs, such as PEOU (r = 0.567) and FC (r = 0.544), confirming that this construct is conceptually distinct. Facilitating Conditions (FC) exhibit a square root of AVE of 0.778, which also surpasses their correlations with AUET (r = 0.544), PEOU (r = 0.483), and PU (r = 0.086), supporting their conceptual specificity. Similarly, PEOU shows a square root of AVE of 0.906, well above its correlations with FC (r = 0.483), PU (r = 0.469), and AUET (r = 0.567), confirming strong discriminant validity. Lastly, PU has a square root of AVE of 0.908, clearly exceeding its correlations with PEOU (r = 0.469) and AUET (r = 0.346), thus validating its conceptual distinctiveness. These findings demonstrate that each construct in the model captures a unique concept, in accordance with the recommendations of Fornell & Larcker, (1981). Therefore, the measurement structure can be considered robust and conceptually sound.

Table 3: Fornell-Larcker Criterion correlation matrix

	AUET	FC	PEOU	PU	SI
AUET	**0.813**				
FC	0.544	**0.778**			
PEOU	0.567	0.483	**0.906**		
PU	0.346	0.086	0.469	**0.908**	
SI	0.307	0.361	0.242	0.003	**0.782**

Source: Authors' calculations based on SmartPLS 3 analysis results.

2.4. Heterotrait-Monotrait criterion (HTMT):

In addition to the Fornell-Larcker criterion, the discriminant validity of the model was also assessed using the HTMT ratio, which is recognized for its heightened sensitivity to conceptual overlap between constructs Henseler et al., (2015). According to these authors, a maximum threshold of 0.90 is generally accepted; values above this limit may indicate a lack of discriminant validity. In studies requiring stricter methodological rigor, a more conservative threshold of 0.85 is often recommended Tabri & Elliott, (2012). The analysis of HTMT values, presented in the corresponding table, shows that all coefficients fall below the 0.85 threshold, with ratios ranging from 0.065 (between PU and SI) to 0.629 (between AUET and FC). These results suggest an adequate level of differentiation between the model's constructs. Notably, the low values observed for the PU–SI (0.065) and PU–FC (0.177) pairs illustrate a clear conceptual distinction, confirming the absence of redundancy between these dimensions. Overall, the HTMT results reinforce those obtained through the Fornell-Larcker approach, thereby strengthening the measurement model's discriminant validity and methodological robustness.

Table 4. Heterotrait-Monotrait criterion (HTMT)

	AUET	FC	PEOU	PU	SI
AUET					
FC	0.629				
PEOU	0.619	0.517			
PU	0.366	0.177	0.488		
SI	0.364	0.485	0.266	0.065	

Source: Authors' calculations based on SmartPLS 3 analysis results.

2.5. Cross-loading matrix:

The cross-loadings matrix is another tool used to assess discriminant validity. It compares the loading coefficients of each item on its associated construct with those on the other constructs in the model. Specifically, an item should have a higher loading on the construct it is intended to measure than on any other construct, thus demonstrating that it correctly measures the targeted concept. Table 5 shows that for each item, the loading is higher on its corresponding construct than on the others. These results indicate that each item appropriately measures its intended construct, thereby confirming the discriminant validity of all examined constructs.

Table 5: Matrix of crossover loads

	AUET	FC	PEOU	PU	SI
AUET1	**0.865**	0.51	0.506	0.353	0.303

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AUET2	**0.851**	0.488	0.472	0.391	0.239
AUET3	**0.833**	0.486	0.435	0.122	0.263
AUET4	**0.726**	0.359	0.451	0.255	0.151
AUET5	**0.783**	0.337	0.438	0.256	0.286
FC1	0.466	**0.853**	0.393	-0.012	0.324
FC2	0.499	**0.788**	0.558	0.23	0.135
FC3	0.401	**0.807**	0.341	0.076	0.291
FC4	0.277	**0.649**	0.095	-0.105	0.479
PEOU1	0.504	0.388	**0.895**	0.479	0.215
PEOU2	0.54	0.417	**0.934**	0.429	0.248
PEOU3	0.473	0.404	**0.891**	0.383	0.211
PEOU4	0.535	0.442	**0.88**	0.359	0.245
PEOU5	0.525	0.454	**0.914**	0.459	0.206
PEOU6	0.497	0.519	**0.92**	0.443	0.185
PU1	0.28	0.032	0.362	**0.916**	-0.023
PU2	0.323	0.054	0.445	**0.933**	-0.006
PU3	0.286	0.119	0.483	**0.935**	0.001
PU4	0.388	0.147	0.476	**0.931**	0.027
PU5	0.297	0.004	0.333	**0.82**	0.052
PU6	0.284	0.09	0.443	**0.908**	-0.048
SI1	0.217	0.196	0.106	-0.011	**0.717**
SI2	0.211	0.17	0.161	0.032	**0.769**
SI3	0.227	0.319	0.173	-0.033	**0.801**
SI4	0.293	0.404	0.286	0.018	**0.837**

Source: Authors' calculations based on SmartPLS 3 analysis results.

The results indicate that each item has a higher factor loading on its respective construct than on the others, thus confirming the factorial structure of the model.

2.6. Principle of collinearity

The Variance Inflation Factor (VIF) is used to examine the interactions between explanatory variables in a predictive model. A VIF score below 5 is generally considered an indicator of low multicollinearity between constructs, meaning there is no strong correlation between the explanatory variables. Table 6 presents the internal VIF values for the analyzed constructs. The results show that no significant correlation exists between the studied constructs, as all VIF values are below the critical threshold 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 6: Internal VIF values

	AUET	EE	FC	PE	SI
AUET					
FC	**1.573**				
PEOU	**1.804**				
PU	**1.367**				
SI	**1.215**				

Source: Authors' calculations based on SmartPLS 3 analysis results.

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2.7. Hypothesis testing results

The objective of hypothesis validation is to examine the direct causal relationships between the elements influencing the adoption of educational technologies. The results of testing hypotheses H_1, H_2, H_3, and H_4 are presented below.

Table 7: Hypothesis testing results

Assump	Struct. L.	O value	M avg.	SD	T-stat.	p-value	Conf
H_1	FC ➔ AUET	0.324	0.322	0.126	2.568	0.011	Accept
H_2	PEOU ➔ AUET	0.3	0.281	0.16	1.873	0.062	Reject
H_3	PU ➔ AUET	0.17	0.194	0.116	1.458	0.145	Reject
H_4	SI ➔ AUET	0.117	0.135	0.109	1.069	0.286	Reject
H_5	Age ➔ AUET	0.024	0.023	0.103	0.232	0.817	Reject
H_6	YOTE ➔ AUET	-0.003	-0.002	0.094	0.031	0.975	Reject
H_7	Gend ➔ AUET	-0.081	-0.085	0.089	0.908	0.364	Reject

Source: Authors' calculations based on SmartPLS 3 analysis results.

The results of the PLS-SEM analysis, presented in Table 7, shed significant light on the determinants of effective use of educational technologies (EU) by Moroccan university teachers. Firstly, facilitating conditions (FC) exert a positive and statistically significant effect on effective technology use ($\beta = 0.324$; $p = 0.011$). This relationship highlights the importance of available resources, technical support and digital infrastructure in the university environment in fostering the adoption and integration of technological tools. This result corroborates the work of Venkatesh et al., (2003), for whom facilitating conditions are a key determinant of technology adoption in organizational contexts. With regard to perceived ease of use (PEOU), its influence on actual usage is positive but weakly significant ($\beta = 0.300$; $p = 0.062$). This trend suggests that the perceived simplicity of technological tools could contribute to their adoption, although this effect remains secondary to institutional support. This finding is partly in line with Davis, (1989) initial model, according to which ease of use indirectly influences usage through perceived usefulness, but it may reflect here a lower awareness of the tools' functionalities in the Moroccan context. Conversely, perceived usefulness (PU) showed no effect on ease of use. This result indicates that teachers do not clearly identify the pedagogical or professional benefits of using technologies. This lack of effect can be explained by a lack of training or a lack of awareness of the concrete contributions of these tools to their practice. Similar results were observed by Bervell & Umar, (2017) in the African context, highlighting that perceived usefulness is not always enough to trigger actual use, in the absence of a strong institutional strategy. Furthermore, SI does not appear to exert a significant effect on actual usage ($\beta = 0.117$; $p = 0.286$). This suggests that social norms, peer expectations or colleague support do not have a decisive weight in the decision to use technologies. This result diverges from the work of Tarhini et al., (2015), which emphasized the impact of the social environment in technology adoption decisions, and may be explained here by a culture of pedagogical autonomy or the absence of an institutionalized digital leadership policy. Finally, demographic control variables such as age ($\beta = 0.024$; $p = 0.817$), gender ($\beta = -0.081$; $p = 0.364$) and years of experience in university teaching ($\beta = -0.003$; $p = 0.975$) showed no significant effect on the actual use of educational technologies. These results suggest that, in this context, personal characteristics play only a marginal role compared to organizational and perceived factors. This is in line with the observations of Olga Mironova et al., (2012), according to whom the impact of demographic variables may diminish when individuals have a sufficient level of experience or autonomy to adopt a technology regardless of their profile.

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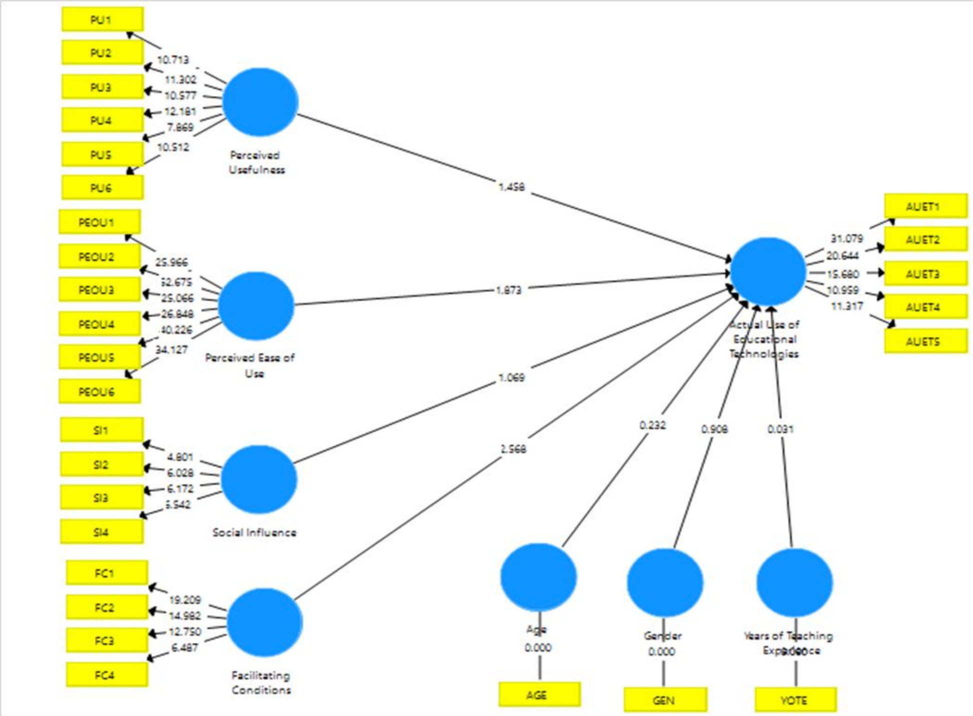

Figure 2. Conceptual framework of the effect of elements on the intention to use.

CONCLUSION:

The study conducted among faculty members at Sidi Mohamed Ben Abdellah University reveals a complex and nuanced picture of educational technology adoption in higher education. Of all the tested variables, only facilitating conditions ($\beta = 0.324$; $p = 0.011$) showed a statistically significant impact on the actual use of digital tools. This result aligns with the findings of Venkatesh et al. (2003), highlighting the crucial role of access to resources, technical support, and infrastructural compatibility in enabling the effective use of educational technologies.

In contrast, classic predictors from the TAM and UTAUT models—such as perceived ease of use ($\beta = 0.3$; $p = 0.062$), perceived usefulness ($\beta = 0.17$; $p = 0.145$), and social influence ($\beta = 0.117$; $p = 0.286$)—did not reach significance. This suggests that, in this context, the mere perception of benefits or user-friendliness is insufficient to drive adoption. As Davis (1989) and Teo (2011) point out, a theoretical appreciation of usefulness does not automatically translate into effective use when structural barriers, inadequate training, or misaligned tools impede practical implementation.

Interestingly, socio-demographic variables such as age, gender, or teaching experience also had no significant effect, indicating that adoption patterns cut across conventional categories. These findings call for a fundamental rethinking of institutional strategies: investment in infrastructures and technical support must be combined with continuous professional development and alignment between technological solutions and the specific needs of each discipline.

Managerial and policy implications are considerable. Universities should institutionalize continuous training focused on real-world applications of educational technologies and adopt systemic strategies that go beyond motivational campaigns. Aligning work environments, curricula, and employability objectives is essential to achieve meaningful technology integration. At the policy level, promoting partnerships between universities and industry will help co-create tailored digital solutions that bridge the gap between academic training and labor market expectations (Villoria-Mendieta, 2024).

This study, however, has limitations. It is confined to a single institution, potentially limiting generalizability to other Moroccan or Global South universities. Its cross-sectional design cannot capture changes over time, especially following interventions like training programs. Furthermore, the model did not include variables such as institutional culture, disciplinary variations, or prior digital experience, which may influence adoption.

Future research could extend the analysis through multi-site comparative studies, longitudinal designs to track changes over time, and mixed-methods approaches integrating qualitative insights. Exploring how different disciplines and institutional contexts shape adoption would also provide valuable depth.

In sum, this study demonstrates that adopting educational technologies is not merely about modernizing tools but about transforming teaching practices to enhance employability and align university curricula with the evolving demands of the digital economy and labor market.

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