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Determinants of Blended Learning Adoption in Algerian Higher Education: An Integrated Technology Acceptance Model and Theory of Planned BehaviorApproach Using Structural Equation Modeling

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Abstract :

This study examines the factors influencing students' adoption of blended learning at the University of Saida, Algeria. To provide a comprehensive understanding, We developed an integrated model based on the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB). The data for this study were collected in 2025.through an online survey of 370 students who had prior exposure to blended learning. The application of Structural Equation Modeling (PLS-SEM) demonstrated that Perceived Ease of Use significantly affects Perceived Usefulness and Attitude. Notably, Perceived Usefulness emerged as the most substantial antecedent of Attitude, which in turn was the key direct driver of Behavioral Intention. Subjective Norms and Perceived Behavioral Control also show significant effects on students' intentions. The model demonstrates strong explanatory power, particularly in predicting Attitude and Behavioral Intention, confirming that adoption is shaped by cognitive, affective, and social-contextual factors. These findings highlight the importance of providing user-friendly tools, high-quality learning resources, and supportive institutional environments. Overall, the study validates the applicability of the integrated TAM-TPB framework in the Algerian higher education context and offers practical guidance for policymakers and educators seeking to strengthen blended learning integration.

Keywords: Blended learning; Technology Acceptance Model; Theory of Planned Behavior; Structural Equation Modeling.

Jel Classification Codes:I23; C38; C83; O33,

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1. Introduction.

Despite the substantial expansion of Algerian higher education—over 100 institutions serving approximately 1.7 million students—significant quality disparities persist, particularly between northern universities and their counterparts in southern and interior regions (Beldjilali, 2022). These inequalities manifest in limited high-speed internet access, under-equipped libraries, and insufficient digital literacy, all of which hinder the adoption of modern educational approaches.

Blended learning (BL), a hybrid model that integrates face-to-face instruction with online components, has been recognised globally as a viable strategy to enhance educational accessibility, flexibility, and engagement (Graham, 2012; Hrastinski, 2019). However, its implementation in Algeria remains obstructed by infrastructural deficits, faculty resistance to pedagogical change, and heterogeneous student readiness for digital learning (Bouhnik, 2014). The COVID-19 pandemic starkly exposed these obstacles, underscoring an urgent need for resilient and contextually adapted educational models.

To understand Algerian students' acceptance of BL, this study integrates the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB). TAM centres on perceived usefulness (PU) and perceived ease of use (PEOU) as core drivers of technology adoption (Venkatesh, 2000), while TPB adds subjective norms (SN) and perceived behavioural control (PBC) as key social and contextual predictors (Ajzen, 1991). Their combination known as C-TAM-TPB (Combined TAM and TPB)—offers a more comprehensive lens for analysingbehavioural intentions, particularly in understudied developing contexts (Nguyen, 2022). While research on BL in developing countries remains limited (Vo et al., 2017; Rasheed et al., 2020), the Algerian setting presents a unique case: the country's strong collectivist culture, acute regional digital divides, and resource-constrained universities make a single-model explanation (either TAM or TPB alone) insufficient. Indeed, although information and communication technologies have transformed education globally (Bhattarai, 2020), successful e-learning adoption in developing nations frequently stalls because of technical, institutional, and psychosocial barriers—a reality that an integrated framework is better positioned to address. Hence, such integration is not merely additive but analytically necessary.

Several critical gaps motivate this study. First, most BL adoption research has been conducted in developed countries, with scant empirical evidence from North Africa, particularly Algeria. Second, existing studies often rely on either TAM or TPB separately, offering only a partial explanation of learners' adoption behaviour. Third, no prior study has systematically examined, within a unified C-TAM-TPB framework, how technological perceptions (PU, PEOU) interact with psychosocial factors (attitude, SN, PBC) to shape Algerian university students' behavioural intention (BI) to adopt BL. Given the ongoing digital transformation of Algerian universities and the persistent regional disparities in technological readiness, a context-grounded, multidimensional understanding is urgently required.

Accordingly, this study addresses the following overarching research question: **What are the key determinants of blended learning adoption among Algerian university students, and to what extent do perceived usefulness, perceived ease of use, attitude, subjective norms, and perceived behavioural control explain students' behavioural intention within a resource-constrained, collectivist higher education context?**.In light of the documented challenges—persistent digital infrastructure deficits in interior universities, uneven digital literacy, and Algeria's strong collectivist orientation—the generic application of technology acceptance models is insufficient. Simply assuming that PEOU leads to PU or that attitude directly drives BI without contextual scrutiny risks masking critical local contingencies. Consequently, this study does not merely replicate the integrated TAM-TPB framework; it explicitly tests six hypotheses derived from the Algerian higher education reality. First, given that unreliable internet access and under-equipped libraries may undermine the very perception of usefulness, we examine whether PEOU still significantly predicts PU (H1) and attitude (H2) in this resource-constrained setting.

Second, because prior exposure to digital learning varies widely among students across regions, we assess whether PU remains the strongest antecedent of attitude (H3) and whether attitude retains its direct influence on BI (H4)—or whether social and control factors override it. Third, in a culture where family, peer, and instructor opinions carry substantial weight, we test the effect of SN on BI (H5). Fourth, acknowledging the acute heterogeneity in access to reliable technology, we evaluate whether PBC significantly shapes BI (H6). By explicitly grounding each hypothesis in the specific constraints and affordances of the Algerian higher education landscape, this study moves beyond theoretical replication to provide actionable evidence for policymakers and educators.

This study makes four key contributions. Theoretically, it advances BL adoption research by validating a C-TAM-TPB framework that integrates technological, social, and control-related determinants. Contextually, it provides novel empirical evidence from Algerian higher education—a severely underrepresented setting. Methodologically, it employs structural equation modelling (SEM) to test the integrated model rigorously. Practically, the findings offer concrete guidance for strengthening digital transformation initiatives, improving technological infrastructure, and enhancing students' readiness for blended learning in resource-constrained environments.

2. Literature Review.

In contrast to the strong emphasis on learner autonomy in models like m-learning, blended learning is characterized by a more formalized pedagogical approach that integrates digital and online media with conventional instruction. Past empirical studies confirm its efficacy, citing the synergy between a collaborative learning environment and promoted autonomy as key drivers of student engagement. The future evolution of blended learning lies in the continuous assimilation of emerging media technologies, which will create increasingly dynamic and effective educational experiences. (Nadlifatin, 2020, p. 221)

Blended learning (BL) has emerged as a transformative educational approach, integrating traditional face-to-face (F2F) instruction with online learning components to optimize student engagement and outcomes. Sharma & Barrett (2007) highlight its role in language education, emphasizing how technology enhances learning while maintaining pedagogical integrity. Similarly,Rasfan Abu Bakar(2021) and Yasin Ozarslan (2009) describe BL as an innovative model that leverages ICT to combine the strengths of offline and online learning, fostering flexibility and accessibility. Hilliard (2015) notes its global expansion, particularly in higher education and professional training, where it addresses constraints like funding and time while improving engagement through collaborative tools.

The pedagogical benefits of BL are widely recognized. Vicki Caravias(2017) and Walib Abdullah (2018) argue that BL caters to diverse learning styles by merging F2F interaction with digital resources, thereby improving student interest and performance. Savvidou&Häggström(2019) further advocate for BL's role in personalized education, supported by digital tools that enable self-paced learning and real-time feedback. Indriani et al (2018) reinforce this, demonstrating BL's effectiveness in vocational education through balanced online and offline activities.

Theoretical frameworks underpinning BL adoption are explored by Charles R. Graham (2012), who identifies institutional strategies and models across educational contexts. Bryan &Volchenkova(2016) trace BL's evolution from correspondence courses to modern digital integrations, emphasizing its adaptability. Meanwhile, DyahPuspitarini (2022) underscores BL's alignment with 21st-century learning paradigms, particularly for tech-savvy generations, while addressing the weaknesses of purely F2F or e-learning models.

Implementation challenges and success factors are critical themes. Zainuddin&Keumala (2018) stresses the importance of strategic planning, technological infrastructure, and faculty training. Whereas Hoic-Bozic et al (2015) showcase successful BL models using LMS and Web 2.0 tools to personalize learning. Institutional support emerges as a recurring determinant of success, as noted

by Ahmed Antwi-Boampong (2023), who identifies faculty motivation and institutional readiness as pivotal for BL adoption in African and global universities.

Student and instructor perceptions are also pivotal. Baragash& Al-Samarraie (2018) find that engagement in multiple delivery modes (F2F, LMS, web-based) positively impacts performance. Bandara&Jayaweera(2024) note BL's benefits—flexibility, cost-effectiveness, and skill development—while cautioning against digital inequality and reduced F2F interaction. Fu Jiang, &Deeprasert (2023) reveal contextual nuances in BL adoption, such as cultural factors influencing Physical Education programs in China.

Finally, institutional adoption frameworks are examined by Chunhui Zhang et al (2022), who advocate for structured strategies, support systems, and iterative evaluation to ensure BL maturity. Mario Vásquez Astudillo (2020)presents a decade-tested pedagogical model emphasizing sequenced, autonomy-driven activities. Conversely, Alayed& Adnan Al-Tit (2021) identify student and institutional variables as key adoption drivers, urging policymakers to address technological and human-resource barriers.

In conclusion, BL represents a dynamic and effective educational model, validated by its adaptability, pedagogical benefits, and capacity to meet diverse learner needs. However, its success hinges on strategic implementation, institutional support, and continuous evaluation to address technological, cultural, and motivational challenges. Future research should explore scalable BL frameworks and longitudinal impacts across disciplines.

3.Conceptual Framework and Research Hypotheses.

3.2. Technology Acceptance Model (TAM).

The Technology Acceptance Model (TAM), introduced by Davis (1989), is one of the most widely recognized frameworks in information systems and technology adoption research (C. T. Chang et al., 2017). Rooted in the Theory of Reasoned Action (TRA), TAM focuses on two key determinants of technology acceptance: Perceived Usefulness (PU), which reflects a user's belief that a system will enhance their performance, and Perceived Ease of Use (PEOU), which measures how effortless a system is to operate (Bhattarai, 2020). External factors influence these perceptions, shaping user attitudes and, subsequently, their behavioral intention to adopt a technology—ultimately predicting actual system usage. TAM has proven highly effective in diverse contexts, including e-learning, where studies confirm that PU and PEOU significantly impact users' willingness to embrace digital tools. For instance, research among Malaysian student teachers validated that both factors, along with attitude, strongly predict technology adoption (Bhattarai, 2020). Similarly, in Libyan higher education, social media's role in e-learning adoption was attributed to its perceived usefulness and ease of use, underscoring TAM's applicability across cultures and technologies (Bhattarai, 2020). Its robustness and adaptability make TAM a foundational model for understanding user acceptance in evolving technological landscapes.(Nguyen, 2022; Bhattarai, 2020)

3.3. Theory of Planned Behavior(TPB).

According to the Theory of Planned Behavior (TPB), behavior is predicted by behavioral intentions, which are in turn influenced by three factors: Attitude, Subjective Norm, and Perceived Behavioral Control (Ajzen, 1991). Attitude refers to an individual's overall evaluation of performing the desired behavior. Perceived Behavioral Control encompasses the beliefs about the presence of factors that may facilitate or impede the behavior, reflecting one's perception of their ability to perform it. Subjective Norm captures the perceived social pressure from significant others to engage or not engage in the behavior (Ajzen, 2015).
In the context of e-learning, user adoption can be inhibited by factors such as a lack of necessary resources or skills (Perceived Behavioral Control) and the influence of opinions from important peers or superiors (Subjective Norm). The TPB framework was developed to explain such

challenges, and both Subjective Norms and Perceived Behavioral Control have been demonstrated to significantly impact behavioral intention. Thus, an individual's intention to use e-learning is formed through a combination of their Attitude toward using it, the perceived Subjective Norms, and their level of Perceived Behavioral Control. The stronger the intention, the more likely the behavior is to be performed. Furthermore, when individuals believe they have a high degree of control over the behavior, they are more likely to carry out their intentions when the opportunity arises (Gollwitzer, 1993; Triandis, 1979; Nguyen, 2022).

3.4. The Integrated Technology Acceptance Model and Theory of Planned Behavior (TAM-TPB) Framework

Both the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB) are widely applied frameworks for examining behavioral intention in technology adoption. TAM emphasizes two central constructs—perceived usefulness (PU) and perceived ease of use (PEOU)—which make it a parsimonious and efficient predictor of usage behavior. In contrast, TPB incorporates additional dimensions—attitude toward the behavior, subjective norms, and perceived behavioral control—providing a more comprehensive view of the social and control factors influencing technology acceptance.

To strengthen both predictive and explanatory power, researchers have developed the Combined TAM–TPB (C-TAM-TPB) model, which integrates the cognitive dimensions of TAM with the attitudinal and social components of TPB. Recent studies confirm the effectiveness of this hybrid approach in diverse contexts. For example, (Tang, 2024)extended the model by incorporating trust and demonstrated its robustness through meta-analysis.(Wang, 2025) applied the integrated model to examine the effects of achievement motivation and framing on students' intentions to use e-learning platforms. (Lv, 2024) validated the C-TAM-TPB framework in the context of blended learning adoption among higher education students. Similarly(Porkodi, 2024), through a systematic review and meta-analysis, identified PU, PEOU, and attitude as the most significant predictors of behavioral intention, thereby reinforcing the explanatory strength of the combined model.

Integration of TAM and TPB has been explored in different ways: some studies combine all five constructs from the two models, while others link TAM's variables directly with the attitude component of TPB to establish a unified framework. The present study adopts the latter approach, as it is more widely supported in the literature and has demonstrated strong empirical validity (Nadlifatin, 2020). This integrated perspective allows for a more nuanced understanding of students' intention to adopt blended learning, capturing both cognitive perceptions and social influences in technology acceptance.

3.5. Researchhypotheses.

According to the integration of the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB), this study examines how their combined variables influence behavioral intention to adopt blended learning. The research model evaluates both the direct effects and interactions between TAM's core components - perceived usefulness (PU) and perceived ease of use (PEOU) - and TPB's key elements of attitude, subjective norms, and perceived behavioral control (PBC). The proposed hypotheses suggest that: (1) PU and PEOU significantly shape positive attitudes toward blended learning; (2) these attitudes, along with subjective norms and PBC, directly strengthen adoption intention; and (3) PU maintains an independent effect on intention beyond its influence through attitude. Furthermore, the model investigates potential moderating effects, where subjective norms may intensify PU's impact on intention, while PBC could amplify PEOU's role. This unified C-TAM-TPB approach aims to demonstrate greater explanatory power than either model alone, providing a more complete framework for understanding the technological,

social, and control factors that drive blended learning acceptance.. these hypotheses can be listed as follows:

H1: PEOU has a significant positive effect on PU

H2: PEOU has a significant positive effect on the AT

H3: PU has a significant positive effect on the AT

H4: AT has a significant positive effect on BI

H5: SN has a significant positive effect on BI

H6:PBC has a significant positive effect on BI

These hypotheses that indicated in Fig.1. Systematically examine both the independent and interactive effects of technological perceptions (PU, PEOU) and psychosocial factors (attitude, subjective norms, PBC) on adoption intention, providing a comprehensive test of the integrated model's predictive power.

3. Material and Method.

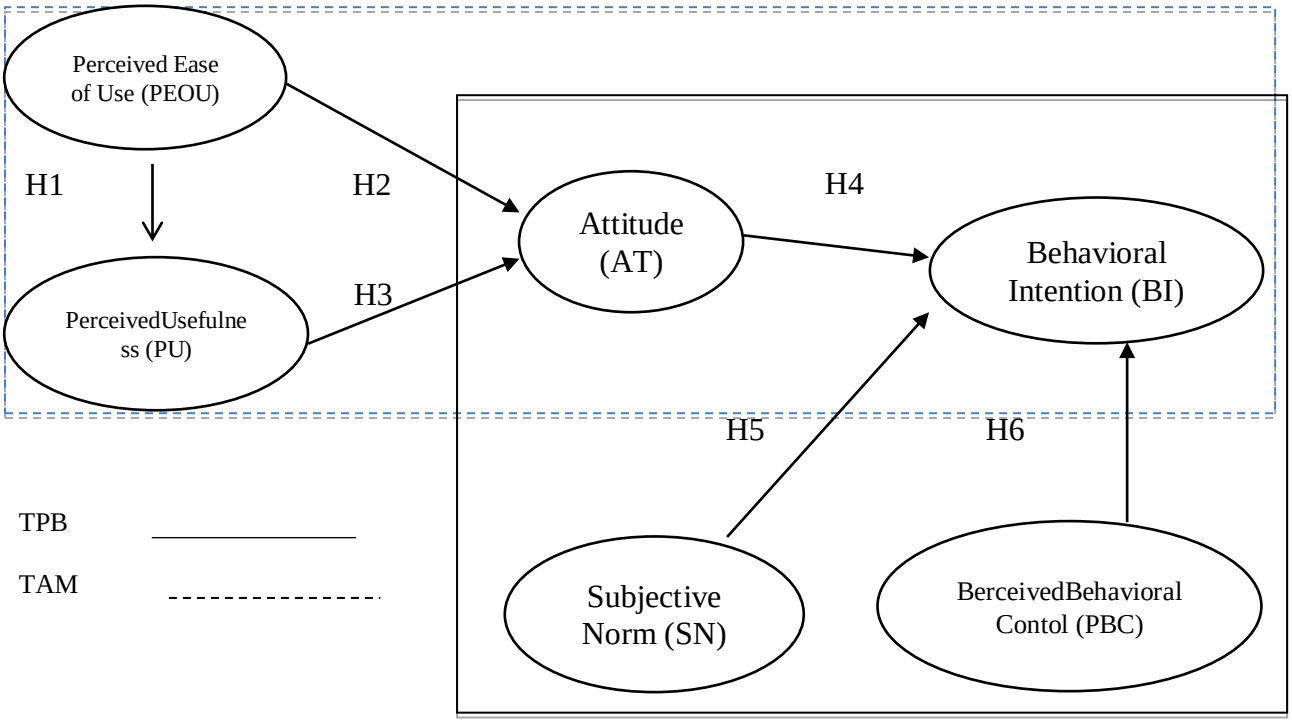
3.1. Data collection.

This study employed Dr. Moulay Tahar University of Saida as a case study, collecting data via a survey administered at Dr. Moulay Tahar University of Saida. Using purposive sampling, 370 students with blended learning experience from the Faculties of Economic, Commercial, and Management Sciences (n=150), Science and Technology (n=110), and Arts and Languages (n=110) were surveyed in 2025. Constructs from the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB) were measured using a 21-item questionnaire on a five-point Likert scale. The measured variables included Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Attitude (AT), Subjective Norm (SN), Perceived Behavioral Control (PBC), and Behavioral Intention (BI).To ensure robustness, the model's reliability and validity were rigorously tested. Internal consistency was confirmed with Cronbach's alpha and Composite Reliability (CR) thresholds of 0.70 (Hair J. F., 2010), while indicator reliability was ensured by removing items with factor loadings below 0.70 (Hair J. F., 2014). Convergent validity was established with Average Variance Extracted (AVE) values ≥ 0.50 (Fornell, 1981), and model fit was assessed using acceptable thresholds for GFI (≥0.90), CFI, and AGFI (≥0.80) (Hair J. F., 2010). Finally, the research hypotheses were examined using Structural Equation Modeling (SEM) to analyze the complex relationships within the integrated TAM-TPB framework.

3.2. Proposed Research Model.

This research examines an integrated framework combining the core constructs of the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB). The proposed model (Figure 1) hypothesizes that a user's Behavioral Intention (BI) to adopt a technology is directly shaped by their Attitude (AT), Subjective Norm (SN), and Perceived Behavioral Control (PBC). By synthesizing these two theoretical foundations, the model enables a comprehensive examination of the cognitive and social determinants of technology adoption, offering a more complete explanation of user behavior.

Figure 1. The proposed model



Source: Authors' own creation.

3.3. Conceptual of Model Variables.

a. Subjective Norms (SN).

Subjective Norm (SN) is a component of social influence representing the perceived social pressure to perform or avoid a particular behavior (Ajzen, 1991). In the context of e-learning, stakeholders—such as peers, instructors, or administrators—can significantly influence a learner's decision to adopt an e-learning system during their evaluation process. The Theory of Planned Behavior (TPB) incorporates SN, positing that it can alter an individual's behavior by shaping their behavioral intentions (Rivis& Sheeran, 2003). Empirical evidence supports this, with several studies identifying SN as one of the most influential predictors of Behavioral Intention to Use (BI) e-learning systems (Cheon et al., 2012; Grandon et al., 2005; Lee, 2010; as cited in Nguyen, 2022, p. 303).

b. Perceived Behavior Control (PBC).

Perceived Behavioral Control (PBC) refers to an individual's assessment of the ease or difficulty of performing a specific behavior (Cheon et al., 2012). It encompasses the belief in one's ability to execute a task, which significantly influences behavioral outcomes (Ajzen, 2002). Research has frequently linked PBC to technology adoption, highlighting its connection to psychological attributes and student beliefs concerning perceived enjoyment and competence (Al-Azawei et al., 2017; Gist, 1989; Grandon et al., 2005). Individuals who are confident in their capacity to learn a new skill or who believe they possess the necessary resources are more likely to develop the requisite ability and perform the behavior. Consistent with this, prior research has established that higher levels of PBC are associated with stronger Behavioral Intention to Use (BI) technological systems (Compeau& Higgins, 1995; Gist, 1989; as cited in Nguyen, 2022, p. 303).

c. Perceived Ease of Use (PEOU).

Perceived Ease of Use (PEOU) is defined as the degree to which a learner believes using a particular technology would be free of effort (Davis, 1989). In an e-learning context, PEOU

represents a key motivational factor, reflecting the student's assessment of the technology's usability. Empirical studies have consistently highlighted its significant role; for instance, PEOU was identified as a strong predictor of Behavioral Intention to Use (BI) technology (Chang et al., 2012) and has been found to considerably influence a user's intention to accept technology (Elkaseh et al., 2016). According to the Technology Acceptance Model (TAM), PEOU also positively influences Perceived Usefulness (PU), suggesting that improvements in usability can enhance perceptions of utility and performance. Furthermore, prior research has established a favorable correlation between PEOU and Attitude Toward Use (AT) in e-learning systems (Calisir et al., 2014; Revythi& Tselios, 2019; as cited in Nguyen, 2022, p. 303).

d. Perceived Usefulness (PU).

A foundational concept in technology adoption is Perceived Usefulness (PU)—the degree to which an individual believes a system will improve their performance (Davis, 1989). In the context of e-learning, PU is demonstrated through the system's capacity to enrich the educational experience with timely and relevant support (Chen & Tseng, 2012). Empirical evidence strongly suggests a positive causal relationship: a higher level of PU leads to a more favorable user attitude (ATU) and a stronger behavioral intention (BIU) to adopt e-learning platforms (Hsia et al., 2014; Mahmodi, 2017; Teo et al., 2008). Ultimately, student acceptance is contingent upon the belief that the technology will enhance their academic achievement.

e. Attitude Towards Use (ATU).

Attitude toward use (AT) represents an individual's positive or negative assessment of adopting e-learning technologies. Within the integrated TAM and TPB framework, AT is shaped by perceptions of usefulness and ease of use, serving as a direct antecedent to Behavioral Intention. Empirical evidence suggests that prior experience fosters positive attitudes, which in turn heightens adoption intent (Nguyen, 2022). However, the influence of AT is not absolute; it is moderated by contextual factors. Counterexamples, such as negative attitudes stemming from poor support at the University of Peshawar and the non-significant role of AT in complex courses (Lazim, 2021), demonstrate that the attitude-behavior link is contingent on the quality of instructional support and the nature of the academic subject.

f. Behavioral Intention (BI).

Behavioral Intention (BI) is defined as a user's willingness to engage with an information system and is a direct determinant of actual use (Alharbi& Drew, 2014; Prieto et al., 2016). In the context of e-learning, BI specifically represents a learner's likelihood of utilizing e-learning systems in the present and future (Liao & Lu, 2008). Grounded in the Theory of Planned Behavior (TPB), Subjective Norm (SN), Attitude Toward Use (AT), and Perceived Behavioral Control (PBC) are established antecedents that favorably influence human intentions and possess significant explanatory power (Chen, 2013). Simultaneously, the Technology Acceptance Model (TAM) posits that Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) are significant factors shaping Attitude (AT) toward technology (Davis, 1989). Empirical work confirms that PU and PEOU influence BI indirectly through their effect on AT (Chen, 2013). Consequently, this study adopts the C-TAM-TPB framework, which integrates these relationships by examining the effects of AT, PBC, and SN on BI (Nguyen, 2022).

4. Results and discussion.

This section presents the results of the measurements discussed in Section 3.

Table 1. Descriptive Statistics

Latent variable	Item	Mean	Standard deviation	Excess kurtosis	Skewness
Perceivedease of use	peou1	3.754	0.868	0.676	-0.847
	peou2	3.646	0.928	0.104	-0.788
	Peou3	3.538	1.093	-0.282	-0.739
PerceivedBehavioural Control	Pbc1	3.614	1.047	-0.304	-0.622
	Pbc2	3.586	1.018	-0.117	-0.660
	Pbc3	3.862	0.832	1.740	-1.038
Behavioural intention	BI1	3.892	1.008	0.700	-1.007
	BI2	3.854	0.967	0.455	-0.874
	BI3	3.614	1.122	-0.327	-0.626
	BI4	3.711	1.040	0.042	-0.775
Subjective Norm	SN1	3.443	1.002	-0.217	-0.524
	SN2	3.343	1.054	-0.657	-0.360
	SN3	3.403	1.175	-0.503	-0.573
Perceivedusefulness	PU1	3.951	0.932	1.260	-1.091
	PU2	3.827	0.999	0.391	-0.890
	PU3	3.924	1.008	0.928	-1.088
	PU4	3.919	0.980	1.112	-1.116
Attitude	AT1	3.922	0.943	0.922	-0.971
	AT2	3.838	0.984	1.687	-1.242
	AT3	3.943	0.958	0.604	-0.941
	AT4	3.673	1.117	-0.345	-0.696

Source: Authors' own creation based on SmartPLS outputs

Additionally, the dataset includes demographic information.The sample consisted of 36.2% male participants (coded as 1) and 63.8% female participants (coded as 2). Age was measured in years. The results indicated that 12.2% of respondents were under the age of 20, 81.3% were between 20 and 30 years old, and 6.5% were aged 30 or above.

Table 2. Demographic Analysis

VARIABLE	RESPONSE'S CHOICE	FREQUENCY	PERCENT
Gender	Male	134	36.2%
	Female	236	63.8%
Age	20-years	45	12.2%
	20-30 years	301	81.3%
	30+ years	24	6.5%
specialization	Faculty of Science and Technology	110	40.5%
	Faculty of Economic, Commercial and Management Sciences	150	29.7%
	Faculty of Languages and Arts	110	29.7%

Source: Authors' own creation based on SmartPLS outputs

5.1 .Structural Model Testing.

The following tables contain key results for evaluation purposes. Tables 3 to 6 present the results of a series of statistical analyses that assess convergent validity(CV), discriminant validity(DV), and internal consistency reliability of the measurement models, as well as the explanatory and predictive power of the structural model, in accordance with the guidelines provided by Hair, Hult, Ringle, and Sarstedt (Hair, 2022). The estimations were conducted using the statistical software package SmartPLS (version 4.0.8.8) (C.M. Ringle, 2022).

The data was collected through an online survey based on a questionnaire specifically developed to investigate the key determinants of students' intention to adopt and use technology.

Table 3. Data Reliability and Convergent Validity

Variable	Notation	Items	Cronbach's α (>0.5)	Factor Loadings (>0.6)	Indicator Reliability	Composite Reliability (>0.7)	AVE (>0,5)
Perceived ease of use	PEUOU	PEOU1	0.650	0.752	0.5655	0.811	0.589
		PEOU2		0.794	0.6304		
		PEOU3		0.755	0.5700		
Perceived usefulness	PU	PU1	0.762	0.814	0.6626	0.848	0.584
		PU2		0.715	0.5112		
		PU3		0.753	0.5670		
		PU4		0.771	0.5944		
Attitude toward use	AT	AT1	0.740	0.742	0.5506	0.837	0.562
		AT2		0.811	0.6577		
		AT3		0.730	0.5329		
		AT4		0.713	0.5084		
Subjective Normes	SN	SN1	0.541	0.751	0.5640	0.764	0.520
		SN2		0.716	0.5127		
		SN3		0.695	0.4829		
PerceivedBehavioural Control	PBC	PBC1	0.587	0.729	0.5314	0.781	0.544
		PBC2		0.695	0.4829		
		PBC3		0.786	0.6178		
Behavioural intention	BI	BI1	0.787	0.803	0.6448	0.862	0.611
		BI2		0.790	0.6241		
		BI3		0.714	0.5098		
		BI4		0.815	0.6642		

Source: Elaborated by authors based on the outputs of Smartpls4

The recommended minimum thresholds for reliability and convergent validity are presented in the table. All constructs in the final model exceeded these thresholds. Specifically, all factors in both countries demonstrated strong internal consistency, with Cronbach's alpha values surpassing 0.8. Only one item had a factor loading slightly below 0.7, yet it still met the minimum acceptable criterion. Furthermore, all constructs exceeded the minimum requirements for composite reliability and Average Variance Extracted (AVE).

Subsequently, the model-fit indices were evaluated to assess the degree to which the proposed model aligns with the observed data. The minimum acceptable values for these fit indices were established in Section 3.3. The results of the model fit tests, which meet orexceed these pre-defined thresholds, are displayed in Table 4.

Table 4. Discriminant Validity

	AT	BI	PBC	PEOU	PU	SN
AT						
BI	0.861					
PBC	0.607	0.651				
PEOU	0.690	0.692	0.677			
PU	0.958	0.834	0.556	0.631		
SN	0.677	0.721	0.508	0.512	0.571	

Source: Elaborated by authors based on the outputs of Smartpls4

Fig. 1. Result of Both Models

We assessed the significance of the correlations using the bootstrap method with 1,000 samples and a 95% bias-corrected confidence interval, utilizing the Maximum Likelihood (ML) estimator. The results, illustrated in the model, show that all hypothesized paths are statistically significant, which confirms the robustness of the proposed model. This implies that each relationship among the constructs is not only positive but also reliable in predicting students' acceptance of blended learning. Unlike studies conducted in other contexts, where some hypotheses were rejected due to insignificant correlations, the current findings provide stronger empirical

support for both TAM and TPB constructs within the Algerian context. This outcome highlights that students at the University of Saida recognize the usefulness, ease of use, social influence, and perceived control as coherent factors shaping their attitudes and behavioral intentions toward blended learning. Consequently, the model demonstrates consistent validity and applicability, reinforcing the importance of both technological and social determinants in enhancing blended learning adoption.

Hypothesis Test:

TABLE 5. Structural Model Results and Hypothesis Testing

HYPOTHESIS	ESTIMATE	STDEV	INFERENCE
H1: PEOU →PU	0.444***	0.050	Accepted
H2: PEOU → AT	0.202***	0.048	Accepted
H3: PU →AT	0.631***	0.040	Accepted
H4: AT →BI	0.495***	0.046	Accepted
H5: SN → BI	0.205***	0.044	Accepted
H6: PBC → BI	0.195***	0.043	Accepted
***p< 0.001			

Source: *Elaborated by Authors based on the outputs of Smartpls4*

See Figure 2.

The findings of the structural model provided important insights into the determinants of students' acceptance of blended learning. The analysis demonstrated a significant positive influence of Perceived Ease of Use (PEOU) on Perceived Usefulness (PU) ($\beta = 0.444$, $p < 0.001$).confirming that when students perceive blended learning systems as easy to use, they are more likely to recognize their usefulness. Moreover, PEOU was found to have a positive effect on Attitude (AT) ($\beta = 0.202$, $p < 0.001$), indicating that system simplicity directly enhances students' positive attitudes toward blended learning.

In addition, Perceived Usefulness (PU) strongly influenced students' Attitude (AT) ($\beta = 0.631$, $p < 0.001$), highlighting that students' perceptions of system usefulness play a crucial role in shaping favorable attitudes toward adoption. The results further showed that Attitude (AT) significantly impacts Behavioral Intention (BI) ($\beta = 0.495$, $p < 0.001$), suggesting that positive attitudes strongly drive students' willingness to adopt blended learning tools.

Social and control-related factors also proved to be significant. Specifically, Subjective Norms (SN) were found to positively affect Behavioral Intention (BI) ($\beta = 0.205$, $p < 0.001$), underlining the importance of peer and institutional expectations in motivating students' intention to engage in blended learning. Similarly, Perceived Behavioral Control (PBC) demonstrated a positive effect on Behavioral Intention (BI) ($\beta = 0.195$, $p < 0.001$), indicating that students' confidence in their own abilities and the availability of resources strengthen their intention to adopt blended learning.

Overall, the study confirms that an integrated model combining TAM and TPB provides a robust explanation for blended learning acceptance, wherein Perceived Usefulness and Attitude emerge as the paramount predictors. Therefore, this research focused on identifying the factors and their interrelationships that influence the adoption and acceptance of blended learning in academic activities among students at the University of Saida, Algeria. The findings highlight that system developers bear the responsibility of designing platforms that are simple, user-friendly, and easy to navigate, thereby facilitating students' engagement. Furthermore, the development of ICT infrastructure by educational institutions and relevant sectors is essential to ensure broader accessibility, which in turn can enhance students' learning performance and effectiveness. Interestingly, students' perceived usefulness of blended learning did not show strong support for

their behavioral intention to adopt it, suggesting that usefulness alone may not be sufficient to drive adoption. Overall, the results provide robust evidence for the proposed factors that promote the effective implementation of blended learning in higher education.

*5.2.*Structural Model assessment.

Figure 2 illustrates the results of the structural equation modeling (SEM), which includes all latent constructs, the standardized path coefficients between them, the factor loadings between observed indicators and their corresponding constructs, as well as the coefficient of determination (R^2) for each endogenous variable (Hair J. F., 2017) .Table 3 summarizes the model's explanatory power, displaying the R^2 values for the endogenous latent variables as accounted for by their respective independent constructs. To examine the hypothesized relationships among the constructs, path coefficient analysis was utilized. The significance of these relationships was tested through a bootstrapping procedure, a non-parametric resampling technique that allows for robust estimation of standard errors and confidence intervals in partial least squares structural equation modeling (PLS-SEM) (Hair J. F., 2017).Bootstrapping is particularly useful when data do not meet the assumptions of normality, as it enables the assessment of the stability and significance of parameter estimates. As shown in Table 7, the analysis reports the path coefficients (β), t-statistics, p-values, and corresponding decisions regarding each hypothesis. Based on the conventional 5% significance threshold ($p < 0.05$), a t-value greater than 1.657 is required for a hypothesis to be deemed statistically significant (Hair J. F., 2017).

The results of the proposed model demonstrate a reasonable explanatory power for the endogenous variables, as indicated by the obtained R^2 values. As presented in Table 5, the coefficient of determination (R^2) reached 55.2% for attitude (AT), 51.4% for behavioral intention (BI), and 19.7% for perceived usefulness (PU). These values suggest that the model is capable of explaining a substantial proportion of the variance in attitude and behavioral intention, while its explanatory power for perceived usefulness remains relatively modest. Overall, the results support the model's appropriateness for explaining individuals' behavior toward the adoption of blended learning systems.

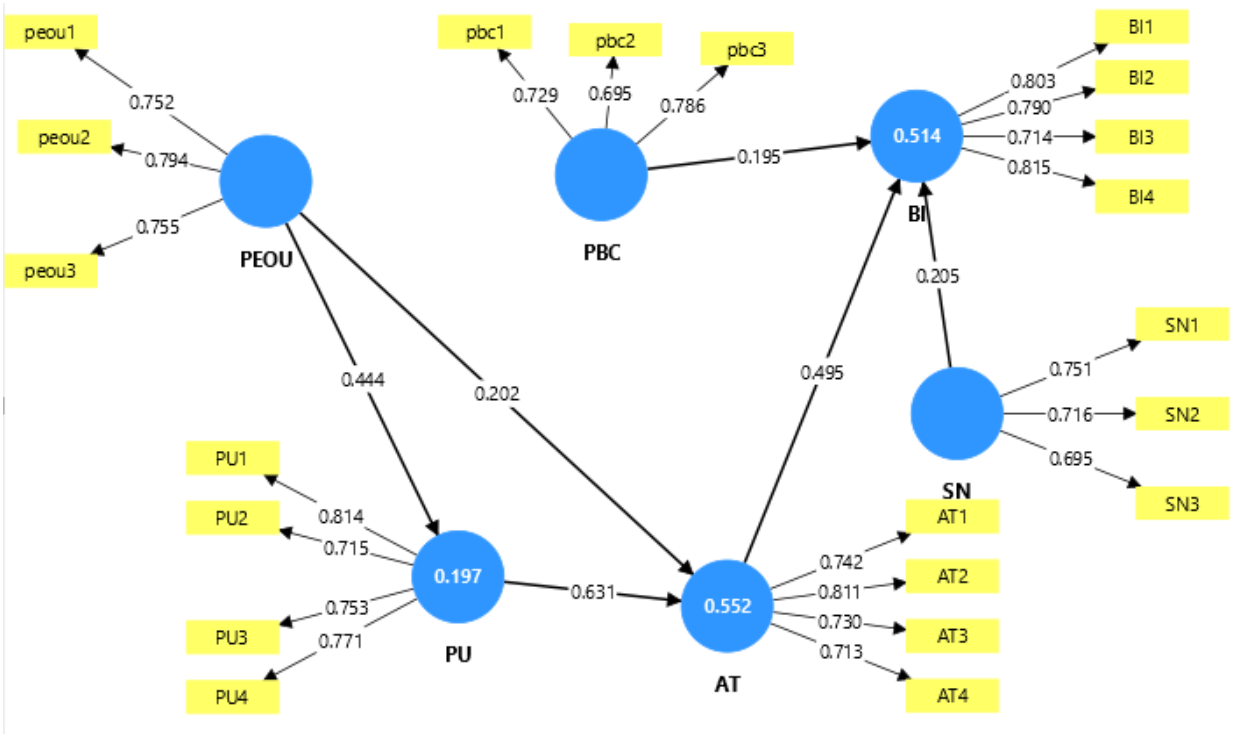
TABLE 6. Coefficient of Determination (R2)

CONSTRUCT	R-square
AT	0.552
BI	0.514
PU	0.197

Source: Prepared by Authors based on the outputs of **Smartpls4**

In line with the literature, the predictive capability of a research model is generally assessed by examining the coefficient of determination (R^2) for endogenous constructs, while the hypothesized relationships are evaluated through path coefficients (Hair J. F., 2017, pp. 153-155)(Henseler, 2009). Previous studies have often reported higher R^2 values for comparable models. However, in the present study, the R^2 values range from 0.552 to 0.197, indicating modest to weak predictive power. Importantly, scholars (Hair J. F., 2017, p. 158)(Chin, 1998) caution against relying solely on R^2 as an indicator of model quality, highlighting instead the need for a holistic evaluation that considers multiple fit indices and the theoretical soundness of the model.

Figure 2. Structural model of the constructed in SmartPLS software



Source:Prepared by authors based on the outputs of Smartpls4

5.3. Discussion.

Hypothesis testing results, summarized in Table 5, indicate that the majority of proposed paths were statistically significant. Based on data from 370 students at the University of Saida analyzed via Structural Equation Modeling (SEM), these findings affirm the utility of combining TAM and TPB to understand the drivers of blended learning acceptance. The analysis showed that Perceived Ease of Use (PEOU) had a significant effect on both Perceived Usefulness (PU) and Attitude (AT), while Perceived Usefulness (PU) emerged as a strong determinant of positive attitudes toward blended learning. Furthermore, Attitude (AT) was found to exert a substantial influence on Behavioral Intention (BI), underscoring its mediating role in students' adoption of technology.

The comprehensive analysis of the data provides robust empirical support for the integrated research model, confirming the significant roles of both technological perceptions (from TAM) and social-contextual factors (from TPB) in shaping students' behavioral intentions towards blended learning at the University of Saida. The model demonstrates strong psychometric properties, as evidenced by the satisfactory levels of internal consistency reliability, convergent validity, and discriminant validity for all constructs. Specifically, all composite reliability scores exceeded the 0.7 threshold, and Average Variance Extracted (AVE) values were above 0.5, confirming that the measures are both reliable and distinct from one another.

The structural model evaluation yielded compelling insights into the hypothesized relationships. The path analysis reveals that Perceived Ease of Use (PEOU) serves as a foundational antecedent, exerting a significant positive influence on both Perceived Usefulness ($\beta = 0.444$, $p < 0.001$) and Attitude ($\beta = 0.202$, $p < 0.001$). This indicates that when students find the blended learning platform intuitive and straightforward to navigate, they are more likely to recognize its practical benefits and develop a favorable disposition towards it. Furthermore, Perceived Usefulness (PU) emerged as the most potent predictor of Attitude ($\beta = 0.631$, $p < 0.001$), underscoring that the platform's perceived utility in enhancing academic performance is paramount in cultivating a positive attitude.

The model also successfully captures the critical pathways to adoption intention. A positive Attitude was found to be the strongest direct driver of Behavioral Intention ($\beta = 0.495$, $p < 0.001$), acting as a powerful mediating mechanism between students' cognitive beliefs (ease of use and usefulness) and their decision to adopt the technology. Importantly, the social environment and individuals' sense of control are also confirmed as vital. The significant effects of Subjective Norms ($\beta = 0.205$, $p < 0.001$) and Perceived Behavioral Control ($\beta = 0.195$, $p < 0.001$) on Behavioral Intention highlight that encouragement from peers and instructors, coupled with students' confidence in their own abilities and access to necessary resources, are crucial motivators for adoption.

The explanatory power of the model, as indicated by the R^2 values, is particularly noteworthy for the key endogenous variables. The model explains a substantial 55.2% of the variance in Attitude and 51.4% in Behavioral Intention, which denotes a strong predictive capability. While the R^2 for Perceived Usefulness (19.7%) is more modest, this is not uncommon, as PU is often influenced by external factors beyond just ease of use. Overall, these values affirm the model's robustness and relevance within the Algerian context.

The path model presented in the image illustrates the results of a Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis, testing an integrated framework that combines the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB). The model examines the key determinants of students' behavioral intention (BI) to adopt blended learning. The numerical values on the arrows between latent constructs (e.g., PEOU → PU = 0.444) represent standardized path coefficients (β), which indicate the strength and significance of the hypothesized relationships. The values next to the measured items (e.g., PEOU1 = 0.752) are outer loadings, confirming that the indicators are reliable measures of their respective constructs, with all values exceeding the critical threshold of 0.6.

Total, indirect and Direct Effects and Hypothesis Testing

Direct effects:the directs effects represent the immediate impact of one construct on another. The analysis reveals several significant direct effects, leading to clear conclusions on the proposed hypotheses:

- **H1: PEOU → PU** The hypothesis is **strongly supported**, as Perceived Ease of Use exerts a significant positive effect on Perceived Usefulness, indicating that students who find the system easy to use are more likely to perceive it as useful for their studies.
- **H2: PEOU → AT:** This hypothesis is **supported**. Ease of Use directly fosters a positive Attitude toward using the technology, though this effect is weaker than its impact on Usefulness.
- **H3: PU → AT:** This hypothesis is **strongly supported**. Perceived Usefulness is the most powerful direct driver of Attitude, confirming that the primary factor shaping a positive disposition is the belief that the system will enhance learning performance.
- **H4: AT → BI:** This hypothesis is **strongly supported**. Attitude is the strongest direct predictor of Behavioral Intention, highlighting that a student's overall positive evaluation is the most immediate antecedent of their decision to use blended learning.
- **H5: SN → BI:** This hypothesis is **supported**. Subjective Norms have a significant, though modest, direct effect on intention, underscoring the importance of social influence from peers, instructors, and the university.
- **H6: PBC → BI:** This hypothesis is **supported**. Perceived Behavioral Control also has a significant direct effect, indicating that students' confidence in their ability to use the system and the availability of necessary resources directly increase their intention to adopt it.

Indirect and Total Effects

The analysis identified significant indirect effects within the model, indicating that constructs exert influence through mediating variables. The total effect, representing the overall impact, is the aggregate of direct and all indirect effects.

- **Indirect Effects:** The most notable indirect effect is the role of **Attitude as a mediator variable**.
    - **PEOU → AT → BI:** Perceived Ease of Use has a meaningful indirect effect on Behavioral Intention through its positive influence on Attitude.
    - **PU → AT → BI:** Perceived Usefulness exerts a very strong **total indirect effect** on Behavioral Intention, which is its only pathway to influence BI. Since there is no direct path from PU to BI, its entire influence is channeled through the formation of a positive Attitude.
    - The effects of SN and PBC appear to be primarily direct, with minimal indirect effects through other constructs in this specific model.
- **Total Effects:** When considering both direct and indirect pathways, the ranking of the most influential constructs on Behavioral Intention (BI) is likely:
    - ✓ **Attitude (AT)** (strong direct effect)
    - ✓ **Perceived Usefulness (PU)** (very strong indirect effect via Attitude)
    - ✓ **Perceived Ease of Use (PEOU)** (significant direct effect on AT and PU, and indirect on BI)
    - ✓ **Subjective Norms (SN)** (modest direct effect)
    - ✓ **Perceived Behavioral Control (PBC)** (modest direct effect)

Globally, all six hypotheses are supported, validating the integrated TAM-TPB model within the Algerian higher education context. The results paint a clear picture: while social Norms (SN) and a perceived behavioral control (PBC) are important direct motivators, the cognitive-affective chain reaction is paramount. Ease of Use boosts Usefulness, and together they are the primary architects of a positive Attitude, which in turn is the most critical direct precursor to Behavioral Intention. This confirms that for blended learning adoption to succeed, institutional strategies must focus not only on providing robust infrastructure and promoting a supportive culture but, most importantly, on ensuring that the technological platforms are genuinely useful and exceptionally easy to use, as these factors fundamentally shape student attitudes and intentions.

5. Conclusion.

This study aimed to identify the determinants of blended learning (BL) adoption among Algerian university students by integrating the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB) within a unified C-TAM-TPB framework. Analysing data from 370 students at the University of Saïda using structural equation modelling (PLS-SEM), the results support all six hypotheses. Perceived usefulness (PU) emerged as the strongest antecedent of attitude ($\beta = 0.631$), while attitude was the most powerful direct predictor of behavioural intention (BI) ($\beta = 0.495$). Subjective norms (SN) and perceived behavioural control (PBC) also exerted significant, albeit modest, direct effects on BI ($\beta = 0.205$ and $\beta = 0.195$, respectively). The model explained 55.2% of the variance in attitude and 51.4% in BI, indicating strong explanatory power, while its ability to predict perceived usefulness ($R^2 = 19.7\%$) was more modest.

The key contribution of this study is contextual. In a resource-constrained, collectivist setting such as Algeria, students' adoption of BL cannot be understood through technological perceptions alone. The significant effects of SN and PBC confirm that social influence and control beliefs play indispensable roles, and the cognitive-affective chain (PEOU → PU → AT → BI) remains robust despite infrastructural deficits. Notably, PU did not directly predict BI but operated fully through

attitude, suggesting that Algerian students do not adopt blended learning purely for utilitarian reasons; rather, positive attitudes mediate the translation of perceived usefulness into intention. This finding reinforces the central mediating role of attitude in the C-TAM-TPB framework and highlights the importance of fostering favourable affective responses alongside demonstrating functional utility.

Practically, the results imply that investing solely in hardware or internet connectivity is insufficient. Institutions must simultaneously pursue four complementary strategies: (a) designing user-friendly platforms that reduce cognitive load (addressing PEOU); (b) clearly communicating the academic benefits of BL through demonstrations and success stories (addressing PU); (c) cultivating a supportive social environment where peers and instructors actively encourage BL use (addressing SN); and (d) strengthening students' digital skills and confidence through training programmes and reliable technical support (addressing PBC). Without such integrated efforts, even the most functionally advanced systems may fail to generate sustained adoption.

Limitations and future implication

Two main limitations are acknowledged. First, the use of purposive sampling, while appropriate for an exploratory study in an under-researched context, limits statistical generalisability. Future research should employ stratified random sampling across multiple Algerian universities – including northern, interior, and southern institutions – to capture regional variations in technological readiness. Second, the cross-sectional design captures behavioural intentions but not actual usage behaviour. Longitudinal studies are needed to observe whether intentions translate into sustained BL engagement, and mixed-methods approaches combining surveys with qualitative insights would help uncover context-specific barriers. Addressing these limitations would further validate the C-TAM-TPB framework and inform scalable digital education strategies, not only in Algeria but across developing nations facing similar infrastructural and cultural constraints. By grounding a well-established theoretical model in a unique contextual reality, this study provides both a replicable analytical template and actionable evidence for policymakers committed to narrowing the digital divide in higher education.

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