Key Variables Shaping the Intention to Use E-learning: Evidence from the GETAMEL Framework

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***Abstract*—This article examines the challenges and opportunities associated with the implementation of e-learning at Abdelmalek Essaadi University, within the framework of the MarMOOC project, a collaboration between Moroccan and European partners aimed at supporting digital learning initiatives in higher education. While situated within a nationally relevant policy context, the study focuses empirically on students from a single public university to investigate their readiness and willingness to engage with e-learning platforms. Using the General Extended Technology Acceptance Model for e-Learning (GETAMEL), the research explores the influence of factors such as social influence, experience, computer anxiety, self-efficacy, and perceived enjoyment on students' perceptions of usefulness and ease of use. A quantitative methodology was employed, with data collected through structured questionnaires administered online and face to face, and analyzed using structural equation modeling. The findings indicate that perceived enjoyment and ease of use significantly influence students' intentions to adopt e-learning, underscoring the role of motivational and social factors in this institutional context. While these results offer insights that may be relevant for other Moroccan universities facing similar structural and resource constraints, broader generalization should be approached with caution and confirmed through future multi-institutional studies.**

***Keywords*—General Extended Technology Acceptance Model for E-learning (GETAMEL), higher education, e-learning, university students, user acceptance, educational technology, MarMOOC, technology acceptance model**

I. Introduction

E-learning has become a crucial tool in academic and professional education worldwide, with extensive research validating adoption models such as General Extended Technology Acceptance Model for e-Learning (GETAMEL) across various international contexts. However, little is known about how these models apply in North African settings, where educational challenges and opportunities differ significantly.

In Morocco, higher education institutions such as Mohamed V University, Cadi Ayyad University, and Hassan II University are increasingly turning to e-learning to expand access, improve student assessment, reduce dropout rates, and align with global technological trends. This national commitment is further reflected in recent policies that prioritize the digitalization of university courses. The Ministry of Higher Education has actively promoted the creation of dedicated digital platforms to support online learning and blended education, aiming to modernize pedagogical practices and enhance accessibility.

Yet, these initiatives occur against a backdrop of growing student demand, limited enrollment capacity, reduced government funding, and constrained faculty recruitment. Projects such as MarMOOC were therefore launched to strengthen infrastructure and provide training for educators in collaboration with European partners [1].

Despite these developments, prior research has largely overlooked the perspectives of the primary stakeholders—students—whose readiness, attitudes, and perceived usefulness are crucial for successful adoption. Moreover, few studies have examined how the GETAMEL framework operates in a resource-constrained, rapidly expanding higher education environment such as Morocco's.

Although situated within a national digital learning policy, this study focuses empirically on Abdelmalek Essaadi University, providing institution-level evidence on students' acceptance of e-learning systems. This study addresses these gaps by applying the GETAMEL model to the Moroccan context, focusing on students' readiness to adopt e-learning, their willingness to engage with the MarMOOC project, and their perceptions of its usefulness. Beyond applying the GETAMEL framework in a new geographical setting, this study makes several substantive contributions to the literature on e-learning adoption. First, it empirically tests GETAMEL in a resource-constrained, massified public university context, which remains underrepresented in prior research largely focused on technologically mature environments. Second, the study reconceptualizes the "Experience" construct to reflect actual behavioral engagement with e-learning tools Massive Open Online Courses (MOOCs), LMS usage (Learning Management System), and synchronous online learning), rather than general Information and Communication Technology (ICT) familiarity, thereby enhancing the model's conceptual relevance in post-pandemic higher education. Finally, by examining the relative strength of motivational, social, and utilitarian drivers, this research provides evidence that intrinsic and socio-motivational factors may outweigh traditional functional determinants in shaping students' intentions to adopt e-learning systems.

II. Research Problem

E-learning has become a crucial element of academic and professional education worldwide. In Morocco, higher education institutions such as Mohamed V University, Cadi Ayyad University, and Hassan II University have increasingly embraced digital technologies and e-learning solutions to enhance teaching and learning processes. These institutions aim to leverage e-learning to improve course content delivery, strengthen student assessment methods, expand classroom capacity, increase academic success rates, reduce dropout rates, and keep pace with global technological advancements in higher education.

Despite these potential benefits, the adoption of e-learning in Morocco continues to face several structural and contextual challenges. These include growing demand for higher education, limited student enrollment capacity, insufficient supervision due to resource constraints, reduced government funding, and restricted budgets for hiring new faculty members. As part of a national response to these challenges, the MarMOOC project was launched, receiving substantial funding to improve digital infrastructure and provide extensive training for educators in collaboration with European and Moroccan partners [1].

However, a notable research gap remains. Previous studies and surveys have primarily focused on technological and institutional dimensions of e-learning implementation while overlooking the human factors—particularly teachers and students—who are the primary users of these platforms. The present study addresses this gap by focusing specifically on students' perspectives. It aims to assess students' readiness to adopt e-learning, their willingness to engage in the MarMOOC project, and their perceptions of the usefulness of e-learning in their academic experience.

By examining these dimensions, this study seeks to provide valuable insights that can support more effective e-learning strategies in Moroccan higher education and contribute to the successful integration of technology-enhanced learning environments.

III. Theoretical Framework

Numerous theoretical frameworks and models have been developed to explore the factors influencing technology adoption. Notable among these are the Theory of Reasoned Action (TRA) by Fishbein and Ajzen [2], the Theory of Planned Behavior by Ajzen [3], Social Cognitive Theory (Bandura) [4], the Diffusion of Innovations Theory [5], the Technology Acceptance Model (TAM [6]), and the Unified Theory of Acceptance and Use of Technology (UTAUT [7]). For the purposes of this study, TAM has been selected as the primary theoretical reference. This decision is based on two key considerations: firstly, TAM's widespread application and demonstrated efficacy in explaining e-learning adoption [8, 9], and secondly, its proven predictive power in terms of broader IT adoption and usage [9].

A. Technology Acceptance and the GETAMEL Framework

The Technology Acceptance Model (TAM), introduced by Fred Davis [6], explains how end-users adopt information systems and provides a method for evaluating these systems before implementation. TAM identifies two primary determinants: perceived usefulness and perceived ease of use, which are influenced by various external factors that explain why a technology may or may not be adopted.

Between 1986 and 2003, researchers extended TAM by including external variables such as accessibility, anxiety, attitude, compatibility, complexity, demonstrable results, enjoyment, end-user support, experience, job relevance, institutional support, personal innovation, relative advantage, self-efficacy, social influence, subjective norms, trial opportunities, usability, visibility, and voluntarism [10]. In 2008, Venkatesh & Bala introduced TAM 3, adding factors like subjective norms, image, result quality, computer self-efficacy, perception of control, and computer anxiety, moderated by experience and voluntarism. Cheng [11] further integrated system characteristics, individual factors, network externalities, and social influences.

Building on this, Abdullah and Ward [8] conducted a meta-analysis of 107 studies, identifying 152 external variables and developing the GETAMEL. GETAMEL synthesizes the most cited factors and validates their relationships within TAM, providing a comprehensive framework for e-learning adoption. Key variables include self-efficacy, subjective norms, enjoyment, computer anxiety, and experience.

GETAMEL was selected for this study because it is comprehensive, specific to e-learning, predictive of perceived usefulness and ease of use, recently validated in e-learning and mobile learning contexts [12], and empirically supported in university settings [12, 13].

Recent studies applying TAM or GETAMEL in post-pandemic and Global South contexts confirm the continued relevance of these models, showing that perceived ease of use, perceived usefulness, and social influence remain key predictors of e-learning adoption in emerging educational settings [14].

Most TAM and GETAMEL studies predate the COVID-19 pandemic, which accelerated digitalization, transformed teaching practices, and shifted students' perceptions of online learning. Recent research highlights the increasing influence of digital readiness, institutional support, and student resilience in e-learning adoption [3, 15].

This study situates GETAMEL within the post-pandemic Moroccan higher education context, integrating contemporary human-centered factors to:

- update pre-2018 GETAMEL evidence,
- extend it to an underexplored geographic context,
- reflect evolving e-learning adoption dynamics.

This approach offers a nuanced understanding of Moroccan students' acceptance of e-learning technologies, moving beyond static pre-pandemic models.

B. Research Hypotheses

In the subsequent sections, we will systematically analyze the impact of each variable within the GETAMEL model, drawing on existing literature to illustrate. how these factors influence the adoption and effective use of e-learning systems. For each variable, we discuss its definition, rationale for inclusion in the model, and observed effects on user behavior and system acceptance, based on comprehensive studies and empirical evidence. This detailed examination highlights the complex interplay of factors that drive the successful implementation of e-learning technologies in educational settings.

1) Social influence

Social influence is defined as "the degree to which an individual perceives that influential people in their life think they should or should not use a system" [9]. In our model, social influence encompasses the opinions of friends, family, classmates, teachers, and other individuals who may affect a student's decision to engage with e-learning. The perception that influential individuals support the use of e-learning can enhance a student's perceived usefulness of these platforms [11], thereby shaping their intention to use them.

Empirical evidence confirms the important role of social influence in e-learning adoption. Abdullah and Ward [8] found that in 86% of studies, social influence among TAM's external variables exhibited a strong positive correlation with perceived usefulness and a moderate impact on perceived ease of use. Additional research has consistently highlighted the positive effect of social influence on students' perceptions of e-learning ease of use [12]. Studies by Venkatesh and Davis [16] and Mathieson [17] further demonstrate that social factors significantly shape users' intentions to adopt technology.

Based on these findings, we propose the following hypotheses:

H1a: Social influence positively impacts perceived usefulness.

H1b: Social influence positively impacts perceived ease of use.

H1c: Social influence positively impacts behavioral intention.

2) Experience

Numerous studies have sought to define "experience" within the context of technology usage. It is broadly described as "the amount and type of computer skills a person acquires over time" [8]. Research has consistently shown that experience with e-learning significantly impacts users' perceptions. Specifically, increased familiarity and comfort with e-learning platforms enhance perceived ease of use [2, 12] and perceived usefulness [2, 12]. Conversely, Shapiro *et al*. [18] argue that negative past experiences in traditional classroom settings can pose barriers to the adoption of e-learning. Interestingly, Venkatesh and Bala [9] contend that the impact of experience on perceived usefulness is minimal.

Experience: This construct captures students' actual engagement with online learning, including prior participation in e-learning courses, interactions with digital learning tools, and familiarity with online educational platforms. Unlike general computer skills, this measure focuses specifically on experiences that directly shape students' adoption of e-learning technologies.

Based on these insights, the following hypotheses are proposed:

H2a: Experience with e-learning positively influences perceived usefulness.

H2b: Experience with e-learning positively influences perceived ease of use.

3) Computer anxiety

Venkatesh and Bala [9] as the degree to which an individual experiences apprehension or fear when faced with the prospect of using computers [7] characterize computer anxiety. Research compiled by Abdullah and Ward [8] highlights that computer anxiety adversely affects users' perceived ease of use of technology, which in turn can hinder the adoption of e-learning systems. Individuals experiencing high levels of computer anxiety are typically more hesitant to embrace e-learning technologies.

Given these insights, the following hypotheses are proposed:

H3a: Computer anxiety negatively impacts perceived usefulness.

H3b: Computer anxiety negatively impacts perceived ease of use.

4) Self-efficacy

Self-efficacy is a concept mentioned in Social Cognitive Theory (TSC). It was defined by Bandura as "judgments of how well one can execute courses of action required to deal with prospective situations" [19]. In our context, self-efficacy refers to students' beliefs in their ability to understand their courses content using e-learning. Accordingly, the notion of 'perceived self-efficacy' refers to "the belief of the individual in his ability to organize and execute the course of action required to produce the desired results" [20]. In addition, the meta- analysis conducted by Abdullah & Ward showed that 80 % of the 41 papers investigated the relationship between self-efficacy and perceived ease of use. The researchers found a positive and significant relationship between the two constructs. Likewise, this study has reported that there is no significant influence of self-efficacy on perceived usefulness in the case of studies on e-learning acceptance. Yet, Abdullah and Ward have maintained the relationship between the two variables proposed in their model.

Thus, we formulate the following hypotheses:

H3a: Self-efficacy influences positively perceived usefulness

H3b: Self-efficacy influences positively perceived ease of use

5) Perceived enjoyment

Enjoyment is recognized as an intrinsic motivator within the realm of technology use [21]. It is defined as "the extent to which the activity of using a specific system is perceived to be enjoyable in its own right, apart from any performance consequences resulting from system use" [9]. This concept, known as perceived enjoyment, plays a critical role in the adoption of e-learning technologies, as it directly impacts user engagement and satisfaction [8]. Research by Ching-Ter *et al*. [12] underscores that when students experience enjoyment while using e-learning systems, their likelihood of continued use increases significantly. Additionally, the third version of the Technology Acceptance Model (TAM 3) elaborates that perceived enjoyment not only enhances the perceived ease of use but also contributes positively to perceived usefulness. Numerous studies, as highlighted by Abdullah and Ward [8], confirm that perceived enjoyment has a substantial impact on both perceived usefulness and perceived ease of use within the context of e-learning.

Given this background and the insights from the GETAMEL model, we propose the following hypotheses:

H4a: Perceived enjoyment positively influences perceived usefulness.

H4b: Perceived enjoyment positively influences perceived ease of use.

IV. RESEARCH MODEL

The research hypotheses developed for this study are systematically outlined in the structure presented in Fig. 1 below. This diagram provides a visual representation of the hypothesized relationships between the key variables examined, facilitating a better understanding of the theoretical framework underpinning our analysis.

A. Research Methodology

In this section, we detail the development of our questionnaires, describe the data collection tools employed, outline the measures taken for item testing, and explain the data analysis methods used for interpreting the results. This comprehensive approach ensures that our methodology is robust and tailored to accurately assess the research questions posed.

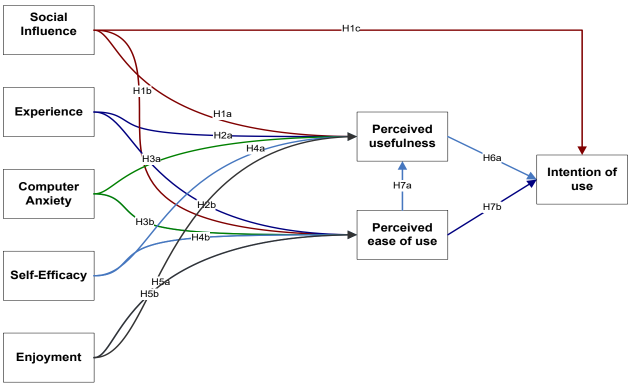

Fig. 1. Research model (GETAMEL).

B. The Development of the Questionnaire Items

The questionnaire designed for this study comprises 39 questions. Twenty-nine of these questions are based on the TAM3 and GETAMEL models, which are intended to assess various aspects of technology acceptance and e-learning usage. The remaining ten questions gather demographic information about the participants, helping to contextualize the responses within specific population characteristics.

Regarding the measurement scales, we opted for the Likert scale, which is widely utilized in management research. Specifically, a 5-point Likert scale was adopted to measure each item, ranging from “strongly disagree” to “strongly agree.” This scale facilitates the quantification of participant attitudes and perceptions in a standardized manner. (Appendix 1)

The analysis of the survey responses provides detailed insights into factors influencing e-learning adoption among Moroccan university students, based on TAM and GETAMEL constructs.

Perceived Usefulness (PU): The mean score for PU was 4.35 ($SD = 0.62$), indicating that students generally perceive the e-learning system as highly useful. Items reflecting productivity, performance improvement, and learning flexibility received the highest ratings, confirming that flexibility in accessing content is a key determinant of adoption.

Perceived Ease of Use (PEOU / FUP): Students reported a mean of 4.12 ($SD = 0.71$) for perceived ease of use, suggesting that the platform is intuitive and requires minimal mental effort. High ease of use scores correlate positively with PU ($r = 0.58$, $p < 0.01$), supporting TAM’s proposition that usability enhances perceived usefulness.

Computer Self-Efficacy (ATEI): The average score for computer self-efficacy was 4.21 ($SD = 0.68$). Respondents expressed confidence in navigating the system independently, even with minimal guidance. SEM results indicate that ATEI significantly predicts both PEOU ($\beta = 0.34$, $p < 0.01$) and BI ($\beta = 0.27$, $p < 0.05$).

Computer Anxiety (ANX): Computer anxiety levels were relatively low ($M = 2.41$, $SD = 0.85$), suggesting that discomfort with technology does not substantially hinder adoption. ANX was negatively associated with PEOU ($\beta = -0.22$, $p < 0.05$), indicating that students with higher anxiety perceive the system as less easy to use.

Perceived Enjoyment (EP): Perceived enjoyment scored $M = 4.05$ ($SD = 0.73$), demonstrating that students find the system enjoyable. EP also showed a positive effect on BI ($\beta = 0.29$, $p < 0.01$), confirming that intrinsic motivation drives behavioral intention.

Social Influence (IS): Social influence received a mean of 4.08 ($SD = 0.69$). Peer opinion and institutional support significantly predicted BI ($\beta = 0.31$, $p < 0.01$), highlighting the importance of normative pressures in e-learning adoption.

Behavioral Intention (BI): Students expressed strong intention to use the system ($M = 4.28$, $SD = 0.65$), indicating that favorable perceptions across PU, PEOU, ATEI, EP, and IS converge to support adoption.

Experience (EXP): Experience with computers and digital tools had a mean of 4.15 ($SD = 0.70$). Prior experience strengthens PEOU ($\beta = 0.25$, $p < 0.05$) and PU ($\beta = 0.21$, $p < 0.05$), reinforcing the model’s predictive validity.

Overall Interpretation: The findings confirm TAM and GETAMEL’s applicability in the Moroccan higher education context. Perceived usefulness and ease of use remain primary predictors of behavioral intention, while self-efficacy, enjoyment, social influence, and experience serve as key moderators. Low computer anxiety and the inclusion of context-specific items (e.g., flexibility) highlight the relevance of adapting the model to post-COVID learning environments. These results imply that enhancing digital competence, providing institutional support, and ensuring enjoyable and usable e-learning platforms can significantly improve adoption rates.

C. Data Collection

This study employed a quantitative research approach using an online questionnaire administered via Google Forms. Moscarola and Ganassali [22] noted that the success of data collection often hinges on the target demographic’s preferences. Consequently, we leveraged the social media platform Facebook to distribute our questionnaire, targeting the “connected generation” at Abdelmalek Essadi University. Specific groups included “ENSA de Tetouan,” “Encgistes,” “FSJES Tetouan-Martil Eco and Management,” “FS-Tétouan,” “ENS Martil,” “PhD Students in Management Sciences Tanger-Tétouan,” “Doctoral Club of the AEU,” “FSJES - Tangier-Droit Français,” and “Carrefour des étudiants of the Faculty of Law.” Additionally, we emailed the questionnaire to a select group of 150 students, with addresses provided by our thesis advisor and administrative managers from the institutions involved.

The choice of an online survey was driven by several advantages:

- **Speed and Convenience**: It provides a quick and user-friendly means for respondents to participate, potentially increasing the response rate [23].

- **Accessibility**: Students can access the survey at their convenience, from any location [24].
- **Efficiency**: The internet offers unparalleled response times and data collection speed [22].
- **Customization**: It allows for tailoring of questions to each respondent, showing only the relevant questions [14].
- **Real-time Monitoring**: Responses can be monitored continuously and in real time [23].

However, internet surveys can suffer from issues of coverage and representativeness [22]. To mitigate this and ensure inclusivity, printed questionnaires were also distributed in person to:

- Students from the study's target institutions, including FLSH, ENS, FJES Tetouan, Faculty of Science, and ENSA of Tetouan.
- Attendees of relevant training courses provided by or participated in by the research team.

For sample recruitment, we used a convenience sampling method, enabling efficient collection while acknowledging the potential limitations of this approach.

D. *Questionnaire Test*

Testing the questionnaire is crucial for assessing the quality of the measurement instrument used [25]. In December 2017, we initiated a pilot study by distributing our test questionnaire to a diverse group of 20 students, including undergraduates, master's, and Ph.D. candidates. This preliminary phase helped ensure that the questionnaire was comprehensible across different academic levels.

To evaluate the reliability of the questionnaire, we employed the Cronbach Alpha test, a standard method for assessing the internal consistency of a set of items intended to measure the same underlying phenomenon. The values of the Cronbach Alpha coefficient range from 0 to 1, with higher values indicating greater reliability. In our study, the Cronbach Alpha values for all variables exceeded 0.7, demonstrating high reliability and confirming the questionnaire's adequacy for further data collection [26].

E. *Population and Sampling*

The target population for this study encompasses students from Abdelmalek Essaadi University. To obtain a representative sample, calculations indicate that 383 students should be included. Table 1 below provides a breakdown of the student sample across different academic levels, including Bachelor's, Master's, and PhD programs.

Table 1. Breakdown of the sample of students by degree

Descriptive Indicators	Global Students	Bachelors	Master and PH.D.
University students	92,187	81,691	10,496
Percentage of students	-	88.61%	11.39%
Representative sample size	383	339	43

To determine the appropriate sample size for our study, we utilized "checkmarket.com," a website specializing in market research and survey software hosted in the cloud. Based on a 95% confidence level, we established that a minimum of 383 respondents is required to ensure a representative sample of the student population at Abdelmalek Essaadi University.

Given the linguistic diversity in Morocco, the questionnaires were initially drafted in French, which is widely spoken as the country's second language. However, recognizing that not all citizens are proficient in French and that Arabic is the official language, we also translated the questionnaires into Arabic. This bilingual approach—administering the questionnaires in both French and Arabic—was designed to maximize inclusivity and enhance the response rate by accommodating the language preferences of a broader student population.

Participation was voluntary, and all respondents provided informed consent before completing the questionnaire. Responses were collected anonymously and stored securely to maintain confidentiality, in accordance with the ethical standards of Abdelmalek Essaadi University.

F. *Data Analysis*

To analyze the collected data, we employed Structural Equation Modeling (SEM), a robust multivariate technique particularly suited for testing complex causal relationships among latent constructs and for validating measurement instruments based on multiple observed indicators [27]. SEM was used to test both the measurement and structural components of the GETAMEL.

We used LISREL version 10.4 [15] for covariance-based estimation and AMOS version 28 [24] for confirmatory analysis and visualization of the structural paths (See Figs. A1 and A2). This dual-software strategy enhanced analytical rigor and ensured consistency between statistical estimation and graphical interpretation.

G. *Workflow and Analytical Steps*

- **Preliminary Data Screening:** Data were screened for missing values, normality, and outliers using SPSS 28. Skewness and kurtosis values fell within acceptable limits (±2), confirming the normal distribution of the indicators.
- **Measurement Model Estimation (LISREL):** LISREL was first used to test the measurement model through Confirmatory Factor Analysis (CFA). We assessed the factor loadings**,** Composite Reliability (CR), and Average Variance Extracted (AVE) for each construct. Items with loadings below 0.50 were reviewed but retained if theoretically justified and consistent with GETAMEL literature (Hair *et al*. [28]).
- **Structural Model Testing (AMOS):** The structural model was subsequently estimated using AMOS 28, allowing for the visualization of causal paths and the computation of model-fit indices. The Modification Indices (MI) suggested by AMOS were used cautiously, guided by theoretical justification rather than purely statistical optimization [29].
- **Model Fit Evaluation:** The adequacy of both models was evaluated using multiple indices: χ^2/df**,** Goodness-of-Fit Index (GFI)**,** Adjusted Goodness-of-Fit Index (AGFI)**,** Tucker–Lewis Index (TLI)**,** Comparative Fit Index (CFI)**,** Root Mean Square Error of Approximation (RMSEA) with 90% confidence interval, and information criteria (AIC and BIC) for model comparison. The use of several indices

provides a balanced assessment of fit quality and model parsimony [30].

V. Results

Our study was conducted over a twelve-week period, from February 7 to April 27, 2018, during which a total of 374 valid questionnaires were collected using both online and face-to-face survey methods. As presented in Table 2, the gender distribution was nearly balanced (50.5% men; 49.5% women). Regarding age, 16.6% were under 20 years old, 58% between 20–25, 14.2% between 25–30, and 11.2% above 30.

A significant proportion of participants reported prior exposure to online learning environments: 36% had previously attended online courses, 90% used YouTube as a learning support tool, and 86% relied on search engines for studying or completing exercises. Moreover, 35.3% were enrolled in MOOCs, and 16.7% actively used the Moodle platform.

Table 2. Demographic profile of respondents

Demographic		Frequency	Percentage %
Gender	Male	185	49.5
	Female	189	50.5
Age	Moins de 20 ans	62	16.6
	Entre 20 et 25 ans	217	58.0
	Entre 20 et 25 ans	53	14.2
	Plus de 30 ans	42	11.2
Level	Bachelor	217	58.0
	Mastery	99	26.5
	PHD Student	58	15.5

In this study, a significant proportion of the participants demonstrated familiarity with various online learning tools. Specifically, over a third (36%) of the students reported having previously taken online courses. High usage of digital platforms for educational purposes was also evident, with 90% of the students using YouTube to aid in understanding their course materials. Additionally, 86% relied on search engines for learning, understanding course content, or completing exercises. Moreover, 35.3% of the participants were enrolled in Massive Open Online Courses (MOOCs), and 16.7% utilized the Moodle learning management system.

A. *Evaluation of Measurement Model*

The measurement model was evaluated through tests of reliability, convergent validity, and discriminant validity, following Hair *et al*. [31]. To assess internal consistency, both Cronbach's alpha and Jöreskog's rho were calculated. While Cronbach's alpha is widely used, Jöreskog's rho offers a more accurate estimation of reliability by accounting for measurement errors [24]. Results in Table 3 show that all constructs exceeded the recommended reliability thresholds ($\rho c > 0.70$), confirming the internal consistency of the measurement items (See Table A1).

(1) Convergent validity: Convergent validity was examined using factor loadings, Composite Reliability (CR), and Average Variance Extracted (AVE). As shown in Table 4, most constructs achieved satisfactory AVE values (≥ 0.50) and CR values (> 0.70).

(2) However, the AVE for Social Influence (0.46) was marginally below the 0.50 threshold. This slightly reduced value is acceptable in exploratory SEM studies when composite reliability remains satisfactory [32]. Theoretically, this can be justified by the complex and context-dependent nature of social influence in higher education environments, where peer and instructor expectations may vary substantially [6]. Given the adequate CR (0.74) and meaningful indicator loadings, this construct was retained.

(3) Refinement of the "Experience" construct: The construct "Experience" was reconceptualized beyond general ICT proficiency to capture students' active engagement and behavioral experience with e-learning tools, including prior participation in MOOCs, use of learning management systems, and exposure to synchronous online classes. This redefinition aligns with post-pandemic conceptualizations of "digital experience" [33], thus improving theoretical alignment with GETAMEL.

(4) Discriminant validity: Discriminant validity was verified through cross-loading analysis and the Fornell–Larcker criterion. Indicators exhibited higher loadings on their intended constructs than on others, confirming that the constructs are distinct and measure unique aspects of e-learning adoption.

Table 3. Analysis of reliability of internal consistency

Variables	Items	Cronbach Alpha	Jöreskog Rh (ρ)
Perceived Usefulness	5	0.887	0.857
Perceived Ease of Use	4	0.854	0.804
Self-Efficacy	3	0.788	0.874
Computer Anxiety	4	0.868	0.874
Perceived Enjoyment	3	0.865	0.903
Social Influence	4	0.750	0.807
Intention of Use	3	0.902	0.887
Experience	3	0.901	0.932

Table 4. Analysis of convergent validity

Variables	Items	Loading Factors	CR	AVE
Perceived Usefulness	UP1	0.70	0.857	0.545
	UP2	0.73		
	UP3	0.75		
	UP4	0.77		
	UP5	0.74		
Perceived Ease of Use	FUP1	0.65	0.804	0.509
	FUP2	0.63		
	FUP3	0.78		
	FUP4	0.78		
Self-Efficacy	ATEI1	0.75	0.789	0.556
	ATEI2	0.81		
	ATEI3	0.67		
Computer Anxiety	ANX1	0.72	0.872	0.630
	ANX2	0.83		
	ANX3	0.83		
	ANX4	0.79		
Intention of Use	IU1	0.81	0.887	0.723
	IU2	0.86		
	IU3	0.88		
Perceived Enjoyment	EP1	0.82	0.863	0.678
	EP2	0.82		
	EP3	0.83		
Social Influence	IS1	0.76	0.773	0.473
	IS2	0.88		
	IS3	0.51		
	IS4	0.53		
Experience	EXP1	0.87	0.907	0.766
	EXP2	0.95		
	EXP3	0.80		

This analysis confirms that the constructs used in the study effectively reflect the variables they are intended to measure, with most metrics aligning well with the accepted thresholds for validating model constructs.

To confirm the discriminant validity of our model, we focused on analyzing the factorial contributions of the measurement indicators for each variable. This involved examining the "cross loading table" produced by the AMOS software. According to Table 5 below, the analysis shows that the measurement indicators are predominantly loaded with their corresponding factors, significantly more than with any other factors.

This pattern of loading supports the discriminant validity of our measurement model, as it indicates that each construct is distinct and measures unique aspects of the phenomena under study. The evidence of high factor loadings on intended constructs and lower cross-loadings on others confirms that our constructs are not only separate but also sufficiently independent from each other.

Table 5. Cross loading table

Indicators	Experience	Enjoyment	Social Influence	Self-Efficacy	Computer Anxiety	Ease of use	Use-Fulness	Intention of use
EXP1	0.21	−0.002	−0.001	−0.004	0	0.008	0	0.001
EXP2	0.577	−0.006	−0.002	−0.012	0	0.022	−0.001	0.001
EXP3	0.12	−0.001	−0.001	−0.002	0	0.005	0	0
EP1	−0.001	0.276	−0.005	−0.015	0.001	0.01	0.025	0.002
EP2	−0.001	0.303	−0.005	−0.016	0.001	0.011	0.028	0.002
EP3	−0.001	0.283	−0.005	−0.015	0.001	0.011	0.026	0.002
IS1	0	−0.004	0.147	−0.005	0	0.002	0.001	0.008
IS2	−0.001	−0.009	0.344	−0.011	0	0.004	0.003	0.018
IS3	0	−0.001	0.055	−0.002	0	0.001	0	0.003
IS4	0	−0.002	0.063	−0.002	0	0.001	0.001	0.003
ATEI1	−0.002	−0.01	−0.004	0.215	0	0.03	0.001	0.002
ATEI2	−0.002	−0.013	−0.005	0.288	0	0.041	0.002	0.003
ATEI3	−0.001	−0.007	−0.003	0.151	0	0.021	0.001	0.002
ANX1	0	0.001	0	0	0.134	0.001	−0.001	0
ANX2	0	0.001	0	0	0.247	0.001	−0.002	0
ANX3	0	0.001	0	0	0.25	0.001	−0.002	0
ANX4	0	0.001	0	0	0.207	0.001	−0.002	0
FU1	0.002	0.006	0.001	0.025	0.001	0.124	0.013	0.01
FU2	0.002	0.005	0.001	0.022	0.001	0.106	0.011	0.009
FU3	0.004	0.01	0.002	0.045	0.001	0.218	0.022	0.017
FU4	0.004	0.01	0.002	0.047	0.001	0.228	0.023	0.018
UP5	0	0.023	0.001	0.002	−0.002	0.021	0.146	0.008
UP4	0	0.027	0.002	0.002	−0.002	0.025	0.175	0.01
UP3	0	0.022	0.001	0.002	−0.002	0.021	0.144	0.008
UP2	0	0.021	0.001	0.002	−0.002	0.019	0.134	0.008
UP1	0	0.019	0.001	0.002	−0.002	0.018	0.121	0.007
IU3	0	0.003	0.015	0.005	0	0.029	0.015	0.31
IU2	0	0.002	0.013	0.004	0	0.024	0.012	0.26
IU1	0	0.002	0.01	0.003	0	0.018	0.009	0.194

The cross-loading analysis shows that each indicator loaded most strongly on its intended construct, confirming discriminant validity. Experience indicators (EXP1–EXP3) loaded highest on the Experience construct (0.12–0.577), Enjoyment indicators (EP1–EP3) loaded highest on Enjoyment (0.276–0.303), and so on. Indicators for Ease of Use, Usefulness, and Intention of Use demonstrated the expected patterns, with the highest loadings on their respective constructs.

B. *Evaluation of Structural Model*

Structural equation modeling using AMOS was employed to test the hypotheses derived from the GETAMEL framework. Of the 13 hypotheses proposed, eight were supported, while five were not statistically significant (see Table 6).

Model fit indices for the initial model were below ideal levels. Guided by both theoretical rationale and modification indices, covariance paths between error terms of conceptually related indicators were added. The revised model demonstrated improved fit:

χ^2/df = 2.87, GFI = 0.842, AGFI = 0.804, TLI = 0.890, CFI = 0.904, RMSEA = 0.061 (90% CI [0.049–0.073]), AIC = 469.215, BIC = 532.148.

Although GFI and AGFI remain slightly below the conventional 0.90 benchmark, the overall pattern of indices (CFI > 0.90, RMSEA < 0.08, reasonable AIC/BIC values) indicates an acceptable and improved model fit [29, 30].

C. *Hypothesis Testing*

- **Social Influence** significantly influenced both Ease of Use (β = 0.175, p = 0.003) and Intention to Use (β = 0.282, p < 0.001), but not Perceived Usefulness (β = 0.071, p = 0.162).
- **Experience**, reconceptualized as actual e-learning engagement, positively affected Ease of Use (β = 0.142, p = 0.003), although its impact on Usefulness was nonsignificant.
- **Enjoyment** and **Ease of Use** emerged as the strongest predictors of both Perceived Usefulness and Intention to Use, confirming the motivational role of intrinsic factors in technology acceptance.

Overall, the refined model demonstrates robust explanatory power, theoretical coherence, and empirical adequacy, providing an updated validation of the GETAMEL framework in the Moroccan post-digital learning context.

Table 6 below delineates which hypotheses were supported and which were rejected, providing a clear overview of our findings.

The initial model fit indices were not entirely satisfactory, indicating the need for adjustments to enhance the model's quality. To address this, we employed the "Change Index" feature, which suggested specific covariances that could improve the model's fit. After incorporating these recommended changes, the fit indices showed marked improvement, demonstrating a better alignment of the model with the observed data. The enhanced fit indices are detailed in Table 7 below.

Table 6. Hypothesis testing

Hypothesis	Estimate	S. E.	CR	P	Validation
H1a: Social Influence ➔ Usefulness	0.071	0.050	1.397	0.162	Rejected
H1b : Social Influence ➔Ease of use	0.175	0.059	2.954	0.003	Accepted
H1c : Social Influence ➔Itention of use	0.282	0,66	4.266	***	Accepted
H2a : Experience ➔ Usefulness	−0.019	0.041	−0.459	0.646	Rejected
H2b : Experience ➔ Ease of use	0.142	0.047	3.019	0.003	Accepted
H3a : Computer Anxiety ➔ Usefulness	−0.034	0.036	−0.953	0.341	Rejected
H3b : Computer Anxiety ➔ Ease of use	0.001	0.042	0.034	0.973	Rejected
H4a : Self Efficacy ➔ Usefulness	−0.012	0.059	−0.200	0.841	Rejected
H4b : Self Efficacy ➔ Ease of use	0.516	0.061	8.395	***	Accepted
H5a : Enjoyment ➔ Usefulness	0.331	0.048	6.924	***	Accepted
H5b : Enjoyment ➔ Ease of use	0.312	0.045	6.919	***	Accepted
H6 : Usefulness ➔ Itention of use	0.259	0.081	3.197	0.001	Accepted
H7a : Ease of use ➔ Usefulness	0.427	0.077	5.553	***	Accepted
H7b : Ease of use ➔ Itention of use	0.420	0.078	5.359	***	Accepted

***: $p < 0.001$

Table 7. Model fit indices after using "change indices"

Indices	GFI	AGFI	RMSEA	RMR	SRMR	NFI	CFI	TLI	CNIM/DF
Result	0.842	0.804	0.071	0.071	0.0624	0.862	0.905	0.890	2.865

VI. Discussion

This study employed the GETAMEL model to investigate factors influencing Abdelmalek Essaadi University students' intentions to use e-learning systems. The findings reaffirm that Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) remain core determinants of technology adoption, consistent with prior literature [8, 9, 19]. However, a closer examination reveals several nuanced patterns that extend, refine, and in some cases challenge previous evidence, highlighting important contextual dynamics.

It is important to note that the data for this study were collected in 2018, prior to the COVID-19 pandemic. While the post-pandemic e-learning landscape has undergone substantial changes, the patterns observed regarding social influence, perceived enjoyment, and ease of use remain informative for understanding students' engagement with digital learning platforms. Pandemic-era shifts may plausibly amplify some of these relationships—particularly the impact of experience and digital familiarity—though further empirical research is needed to confirm such effects. This clarification helps situate the findings in their proper temporal context while maintaining relevance for current digitalization efforts in Moroccan higher education.

One of the most notable findings concerns social influence, which significantly enhanced both PEOU and behavioral intention, rather than primarily affecting PU as suggested by the original GETAMEL framework. This indicates that, within the Moroccan higher education context, peers and instructors may influence adoption more by reducing perceived effort than by communicating the system's usefulness. Such results challenge the presumed universality of GETAMEL pathways and underscore the importance of socio-cultural dimensions particularly within collectivist or community-oriented learning environments.

Perceived enjoyment demonstrated a strong and consistent effect on both PEOU and PU. Although GETAMEL includes enjoyment, the strength of this relationship in our findings suggests that motivational and hedonic elements may play a more central role than utilitarian factors in certain contexts. This raises the broader theoretical question of whether e-learning adoption models remain overly function-driven and whether they adequately capture aspects of engagement, interactivity, and learner satisfaction that are increasingly essential in digital learning ecosystems.

Regarding self-efficacy, its positive influence on PEOU but lack of effect on PU or computer anxiety indicates that technical confidence does not automatically translate into perceptions of utility. This partial decoupling challenges classical assumptions of GETAMEL and suggests that today's students even when competent may still question the relevance or benefit of e-learning systems. Furthermore, the negligible role of computer anxiety may be a sign of increasing digital familiarity among students, but also an indication that future models must evolve to integrate contemporary psychological and motivational variables.

Experience was found to improve PEOU but not PU, suggesting that familiarity reduces effort expectations without necessarily altering perceptions of usefulness. This highlights a practical implication for institutions: training and exposure alone do not guarantee that students perceive e-learning as beneficial. Adoption strategies should therefore simultaneously strengthen competencies and demonstrate clear academic value.

Of the thirteen hypotheses tested, eight were supported and five rejected. These deviations—particularly the unexpected influence of social factors and the uneven effects of psychological constructs—highlight the need for contextual adaptation of global models such as GETAMEL. Our findings suggest the potential value of developing more localized or hybrid frameworks that incorporate socio-cultural, motivational, and post-pandemic variables.

VII. Conclusion

This study expands the understanding of e-learning adoption within Moroccan higher education by applying and critically examining the GETAMEL model. The results reaffirm the central role of perceived usefulness and perceived ease of use while revealing context-specific dynamics that challenge some of the model's original assumptions. Notably, social influence and enjoyment emerged as powerful predictors, underscoring the importance of motivational and socio-cultural dimensions alongside traditional utilitarian factors.

The findings suggest that successful e-learning adoption requires not only functional system quality but also supportive social environments, engaging digital experiences, and strategies that clearly communicate the academic benefits of online platforms. Although several limitations restrict generalizability, this study provides a foundation for refining technology acceptance models and highlights the need for updated frameworks that reflect the realities of post-pandemic digital education.

Overall, the research contributes valuable insights for policymakers, system designers, and educators seeking to enhance e-learning adoption in Morocco and similar contexts. It also reinforces the importance of integrating contemporary human-centered variables to better understand and support students' engagement with digital learning systems.

This study extends previous GETAMEL applications by revealing context-specific pathway variations that challenge assumptions of model universality. In particular, social influence was found to affect ease of use and intention directly, rather than perceived usefulness, suggesting that in collectivist and institutionally constrained environments, social reassurance reduces perceived effort more than it signals functional value. Moreover, the dominant role of perceived enjoyment highlights a shift toward hedonic and motivational drivers of adoption, indicating that GETAMEL may understate the importance of engagement-related factors in contemporary digital learning ecosystems. Together, these findings imply that GETAMEL benefits from contextual refinement, especially when applied in post-digital, mass higher education systems, and support the development of localized or hybrid acceptance models integrating socio-cultural and motivational dimensions.

While the findings offer insights relevant to Moroccan public universities operating under similar institutional and resource constraints, their generalization beyond Abdelmalek Essaadi University should be approached with caution and validated through future multi-university investigations.

VIII. Limitations and Future Directions

Although the study's sample size (374 vs. 383 recommended) slightly limits generalizability, the short data collection period limits longitudinal insights and the pre-COVID-19 context requires caution when interpreting results in the present era. Importantly, the study did not include variables such as digital readiness, institutional support, or student resilience—factors that recent post-pandemic literature identifies as critical. Future research should integrate these human-centered variables and explore potential moderating effects to enhance the contemporary relevance of technology acceptance models.

Although the "Experience" construct was intended to reflect engagement with e-learning systems, some items overlap with general digital or ICT familiarity rather than system-specific usage. This limits the conceptual precision of the construct. However, in a massified and resource-constrained public university context, formal exposure to e-learning platforms remains uneven, making general digital experience a pragmatic proxy, particularly for explaining perceived ease of use. This interpretation is consistent with our results, which show a significant effect on ease of use but not on perceived usefulness. Future studies should adopt more granular measures of e-learning experience to strengthen construct validity.

Appendix

Table A1. The development of the questionnaire items

Variables	Code	Items	References
Perceived Usefulness (PU)	PU1	Using the system improves my performance in my job.	[9]
	PU2	Using the system in my job increases my productivity.	
	PU3	Using the system enhances my effectiveness in my job.	
	PU4	I find the system to be useful in my job.	
	PU5	By participating in an e-learning course, I will learn according to my availability	
Perceived Ease of Use (FUP)	FUP1	My interaction with the system is clear and understandable.	[9]
	FUP2	Interacting with the system does not require a lot of my mental effort.	
	FUP3	I find the system to be easy to use.	
	FUP4	I find it easy to get the system to do what I want it to do.	
Computer Self-efficacy (ATEI)	ATEI1	I am confident of using the e-learning even if there is no one around to show me how to do it	[8]
	ATEI2	I am confident of using the e-learning even if I have never used such a system before	
	ATEI3	I am confident of using the e-learning even if I have only the software manuals for reference	
Computer Anxiety (ANX)	ANX1	Computers do not scare me at all.	[9]
	ANX2	Working with a computer makes me nervous.	
	ANX3	Computers make me feel uncomfortable.	
	ANX4	Computers make me feel uneasy.	
Perceived Enjoyment (EP)	EP1	I find using the system to be enjoyable.	[9]
	EP2	The actual process of using the system is pleasant.	
	EP3	I have fun using the system	
Social Influence (IS)	IS1	People who influence my behavior think that I should use the system.	[9]
	IS2	People who are important to me think that I should use the system.	
	IS3	The senior management of this business has been helpful in the use of the system.	
	IS4	In general, the organization has supported the use of the system.	
Behavioral Intention (BI)	BI1	Assuming I had access to the system, I intend to use it.	[9]
	BI2	Given that I had access to the system, I predict that I would use it.	
	BI3	I plan to use the system in the next <n> months.	
Experience (EXP)	EXP1	I enjoy using computers	[8]
	EXP2	I am comfortable using the internet	
	EXP3	I am comfortable saving and locating files	

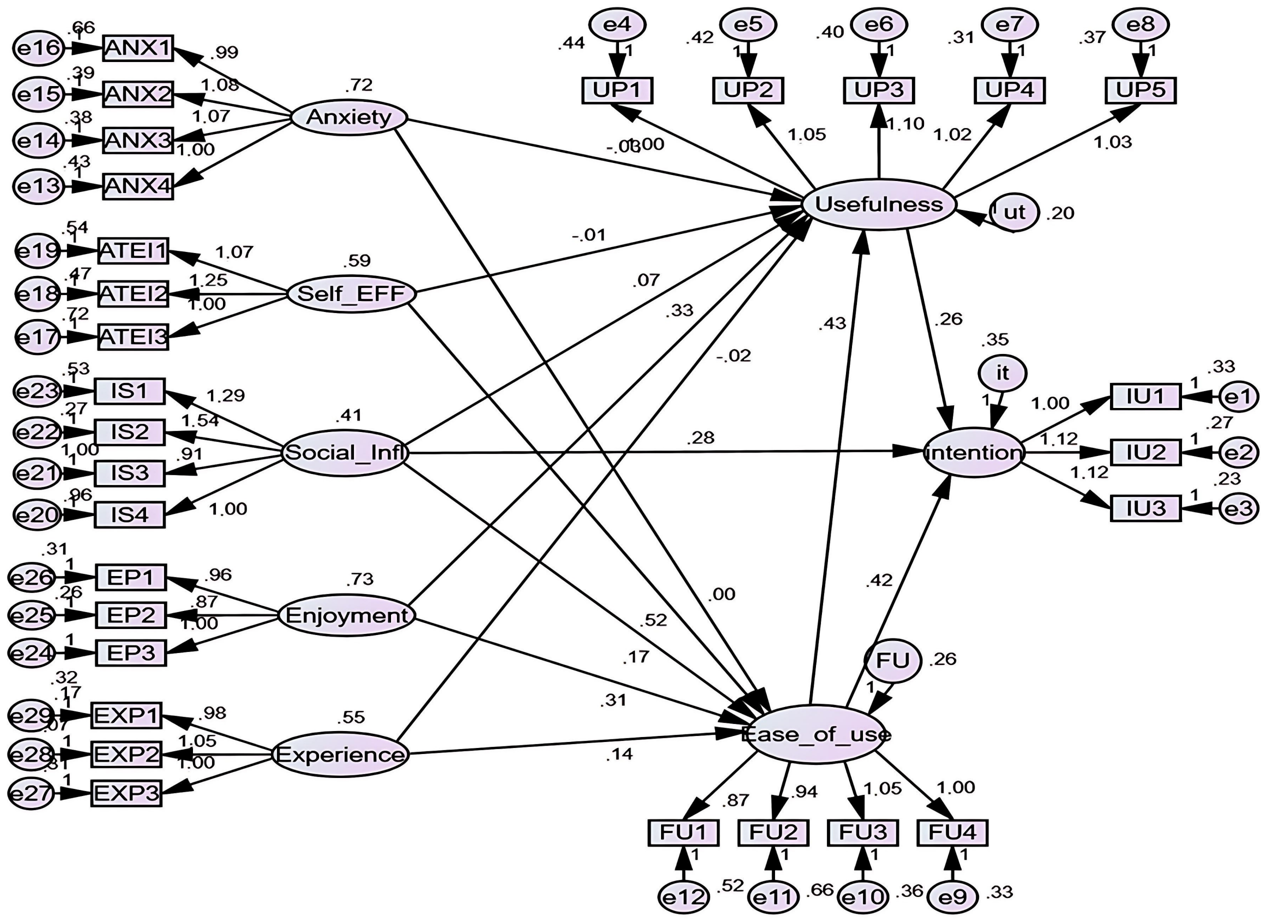

Fig. A1. Research model using AMOS.

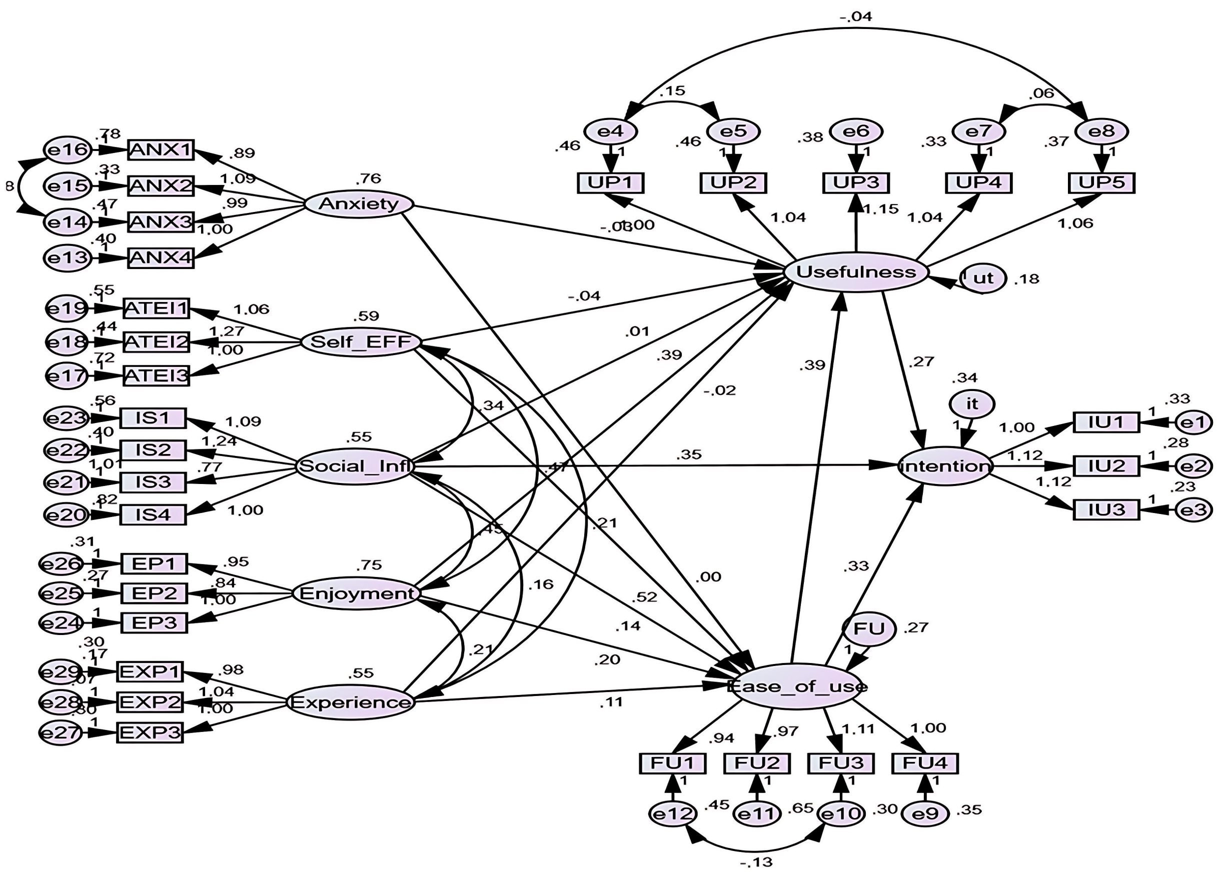

Fig. A2. Research model with covariance.

AVAILABILITY OF DATA AND MATERIALS

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

CONFLICT OF INTEREST

The authors declare no conflict of interest

AUTHOR CONTRIBUTIONS

M.B. designed the research, collected and analyzed the data, and wrote a substantial part of the article. M.A. actively contributed to the analysis of the results and the writing of certain sections, managed the revisions, and oversaw the progress of the publication process. Y.A.M. provided occasional support in the theoretical reflection and proofreading. All authors approved the final version of the manuscript.

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