Acceptance of Artificial Intelligence Tools Among Undergraduates: An Application of the Technology Acceptance Model

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SUMMARY

This study investigated the application of the Technology Acceptance Model (TAM) to assess the acceptance and adoption of Artificial Intelligence tools in educational contexts. The research focused on analyzing the attitudes of university students towards the implementation of AI technologies in teaching and learning processes. **Methodology:** The study used the TAM theoretical framework, focusing on two main constructs: perceived usefulness and perceived ease of use as predictors of intention to use AI tools in education. Correlational and median difference statistical analyses were applied to examine the relationships between these variables in a sample of students. **Key findings:** Results revealed significant correlations between *perceived usefulness* and *intention to use AI*, as well as between *perceived ease of use* and *behavioural intention*. Inferential analysis demonstrates that the external variables *prior experience with technology* and *institutional support* influence *perceived usefulness*, *perceived ease of use* and *intention to use* AI tools in university higher education. In addition, hierarchical regression was used to analyze the moderation of external variables in the TAM model, finding that previous experience with technology significantly enhances the relationship between perceived usefulness and intention to use ($\beta = .35$, $p = .001$), increasing the explained variance to 53% in the final model. On the other hand, student participants, grouped into *academic faculties*, show significant differences in the perception of the TAM variables. **Conclusions:** The study confirms the applicability of the TAM model in the educational context for AI technologies, suggesting that both perceived benefits and usability and institutional support are critical factors in promoting the successful adoption of these tools in academic settings.
Keywords: TAM, Artificial Intelligence, University Higher Education

INTRODUCTION

The integration of Artificial Intelligence (AI) in higher education is transforming traditional teaching and learning paradigms (Zawacki-Richter et al., 2019). However, the adoption of these tools has not been uniform across universities, generating debate about their effectiveness and acceptance.

Problematic situation

Internationally, the integration of digital technology in education has allowed the democratization of access to information, expanding educational coverage and implementing interactivity through learning environments (Araujo Bedoya et al., 2024), which is redefining the future in terms of learning (Vera & García-Martínez, 2022). This technological adoption has generated a paradigm shift in the integration of educational technology (Gros et al., 2020), which has undoubtedly led universities to consider its challenges and opportunities (Carrión Salinas & Andrade-Vargas, 2024).

The implementation of AI tools in higher education varies significantly. Holmes et al. (2019) and Pedreño Muñoz (2022) say that there has been an increase in the adoption of AI in education globally, with countries such as the United States, Spain and China adopting these technologies as intelligent tutoring systems (ITS) and being welcomed by education stakeholders; while, during the 2020-2025 period, generative artificial intelligence has been adopted as a teaching strategy that improves teaching and learning.(Echeverria Quiñonez & Otero Mendoza, 2025).

In Latin America, the integration of technology in university education is in its early stages, with challenges related to technological infrastructure and teacher training (Holmes et al., 2019; Luckin et al., 2016; Pedreño Muñoz, 2022), as well as the student perception indicated by Morocho Cevallos et al. (2023) who state that only 70% of students in the Ecuadorian public sector and 65% in the private sector have identified improvements in teaching methodology using AI tools, showing a variability in the perceptions and experiences of students, who in turn have identified improvements in their performance and academic participation.

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At the local level, it has been observed that universities are beginning to experiment with AI tools, but their widespread adoption still faces barriers, including the adoption and willingness to use AI by university students, of which no Salvadoran studies have been conducted, leading to the next general research question: What are the factors that influence university students' acceptance of artificial intelligence tools according to the Technology Acceptance Model (TAM)?

The specific research questions that guide the objectives of this study are presented below:

1. how do perceived usefulness and perceived ease of use influence university students' intention to use AI tools?
2. What role do external variables, such as prior experience with technology and institutional support, play in the acceptance of AI tools?
3. Are there significant differences in the acceptance of AI tools among students from different academic faculties?

Objectives

Overall objective

To analyze the factors that influence the acceptance of artificial intelligence tools by university students using the Technology Acceptance Model (TAM).

Specific objectives

1. Examine the relationship between perceived usefulness, perceived ease of use, and intention to use AI tools in the university context.
2. Assess the impact of external variables such as previous experience with technology and institutional support on the acceptance of AI tools.
3. Compare the acceptance of AI tools among students from different academic faculties.

Hypothesis system

H1: Perceived usefulness of AI tools is positively related to intention to use by university students.
H2: Perceived ease of use of AI tools is positively related to intention to use by university students.
H3: External variables, such as previous experience with technology and institutional support, are positively related to perceived usefulness and perceived ease of use of AI tools.
H4: There are significant differences in the acceptance of AI tools among students from different academic faculties.

Justification

This study is relevant to the academic and scientific community as it provides crucial information on the factors that influence the adoption of AI tools in higher education. The results inform educators, university administrators and educational technology developers on how to improve the implementation and use of these tools. In addition, the study contributes to the literature on the application of TAM in the context of emerging technologies in education.

Literature review

Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), proposed by Davis (1989), is widely used to explain the adoption of new technologies. The TAM postulates that the intention to use a technology is mainly determined by two factors: perceived usefulness and perceived ease of use. Thus, King & He (2006) consistently confirm their main constructs as predictors of technology adoption.

Previous studies have applied the TAM in the context of higher education. For example, Morales Chan et al. (2018) used TAM to investigate the adoption of cloud-based tools by MOOC students, finding that perceived ease of use and perceived usefulness influence attitudes towards cloud-based tools used in a MOOC. Scheler et al. (2019) used an extension of the TAM to examine the acceptance of digital learning technologies among university teachers. Their findings suggest that perceived usefulness and perceived ease of use are significant predictors of usage intention. Chau identified TAM as one of the most influential models in research on technologies applied to online education or web-based learning (Chen, Zou, et al., 2020, citing Chau, 1996).

Applications of the Technology Acceptance Model (TAM) over the 2020-2025 period have demonstrated adaptability and continued relevance in explaining the adoption of emerging technologies in higher education (Cabero-Almenara et al., 2018). Extensions of the TAM developed during 2022-2023 have incorporated constructs specific to AI tool acceptance, including variables such as positive attitudes among faculty and

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institutional support (Robles Morales, 2025), ethics and trust as moderating variables, and subjective norms as a quadratic variable (Mustofa et al., 2025).

Recent meta-analyses (2024-2025) confirm that perceived usefulness and perceived ease of use maintain their predictive power, while additional factors such as self-efficacy, social norms, and enjoyment emerge as significant predictors of perceived usefulness and ease of use of technology (Santini et al., 2025).

Along the same lines, validation studies of TAM instruments for mobile applications have reported highly positive perceptions and increasing willingness to use educational technologies (León-Garrido et al., 2025).

Technology Acceptance Model (TAM) Extensions

The Technology Acceptance Model (TAM), proposed by Davis (1986), has undergone multiple extensions and refinements since its original conception, with the aim of improving its explanatory power and adapting it to various technological and organizational contexts. These extensions have arisen to address limitations identified in the original model and to incorporate additional factors that influence the acceptance and use of emerging technologies.

TAM2: Theoretical Extension of the Original Model

TAM2 represents the first major extension of the original model, developed by Venkatesh & Davis (2000) with the purpose of explaining in more detail the antecedents of perceived usefulness and providing a more complete understanding of the factors that influence technological acceptance. This extension incorporates two main categories of determinants: social influence processes and cognitive instrumental processes. *Social influence processes* include *subjective norm* (the individual's perception of whether important people think he or she should use the system), *voluntariness* (the degree to which use is perceived as non-compulsory), and *image* (the degree to which use enhances status within the social group). For their part, *cognitive instrumental processes* comprise *job relevance* (degree to which the individual believes the system is applicable to his or her job), *quality of results* (degree to which the system executes relevant tasks correctly), and *demonstrability of results* (tangibility of the results of system use) (Venkatesh & Davis, 2000). Empirical validation of TAM2 was conducted through four longitudinal field studies in different organizations, demonstrating that social influence factors are particularly important during the initial stages of implementation, while cognitive instrumental processes maintain their relevance over adoption time (Venkatesh & Davis, 2000).

TAM3: Comprehensive Integration of Determinants

TAM3, proposed by Venkatesh & Bala (2008), represents a comprehensive integration that incorporates both the elements of TAM2 and the determinants of perceived ease of use, thus providing a holistic view of the factors influencing technological acceptance. This extension identifies *anchors* (variables that act as initial reference points) and *adjustments* (modifications based on direct experience with the system) as explanatory mechanisms of perceived ease of use. Anchors include *computer self-efficacy* (judgment of one's own abilities to use computers), *perceived external control* (beliefs about the availability of resources and organizational support), *computer anxiety* (degree of apprehension toward computer use), and *computer playfulness* (degree to which interactions with computers are perceived as fun). Adjustments include *perceived enjoyment* (extent to which the use activity is perceived as pleasurable) and *objective usability* (comparison of systems based on the actual effort required to complete specific tasks) (Venkatesh & Bala, 2008). TAM3 has demonstrated predictive robustness in diverse organizational and technological contexts, providing a comprehensive theoretical framework for understanding both the cognitive and experiential antecedents of technological acceptance (Venkatesh & Bala, 2008).

UTAUT: Unified Theory of Acceptance and Use of Technology

The Unified Theory of Acceptance and Use of Technology (UTAUT) was developed by Venkatesh et al. (2003) as a result of the conceptual and empirical integration of eight prominent technology acceptance models, including TAM, TAM2, the Theory of Reasoned Action, the Motivational Model, the Theory of Planned Behavior, Social Cognitive Theory, the Theory of Diffusion of Innovations, and a combined model of TAM and TPB. UTAUT proposes four direct determinants of usage intention and behavior: *performance expectancy* (the degree to which the individual believes that using the system will help them achieve improvements in job performance), *effort expectancy* (the degree of ease associated with using the system), *social influence* (the degree to which the individual perceives that important others believe they should use the new system), and *facilitating conditions* (degree to which the individual believes that organizational and technical infrastructure exists to support the use of the system) (Venkatesh et al., 2003). In addition, UTAUT incorporates four key moderating variables: *gender*, *age*, *experience*, and *willingness to use*, which moderate the relationships between the main determinants and the dependent outcomes. Empirical validation of UTAUT showed that this model explains approximately 70% of the

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variance in intention to use, significantly exceeding the explanatory power of previous individual models (Venkatesh et al., 2003).

UTAUT2: Extension for Consumer Contexts

UTAUT2 represents a specific extension of UTAUT developed by Venkatesh et al. (2012) to address the particularities of technology adoption in consumer contexts, where individuals act as end users rather than organizational employees. This extension incorporates three additional constructs that reflect the specific motivations and constraints of consumers. The new constructs include *hedonic motivation* (fun or pleasure derived from using the technology), *price value* (consumers' cognitive trade-off between the perceived benefits of applications and the monetary cost of using them), and *habit* (the extent to which people tend to perform behaviors automatically due to prior learning). Additionally, UTAUT2 eliminates the moderating variable of voluntariness, since in consumer contexts, use is inherently voluntary (Venkatesh et al., 2012). Empirical validation of UTAUT2 in mobile technology contexts demonstrated substantial improvements in the explanatory power of the model, achieving an explained variance of 74% for intention to use and 52% for usage behavior (Venkatesh et al., 2012).

Specific Extensions for Educational Contexts

Various studies have developed specific adaptations of TAM and its extensions for educational contexts, recognizing the particularities of the academic environment and the specific characteristics of students and teachers as technology users. These adaptations have incorporated variables such as *technological self-efficacy*, *attitudes toward online learning*, *institutional support*, and the *quality of the educational system*. Abdullah & Ward (2016) developed an extension of TAM specifically for e-learning, integrating the factors of experience, subjective norm, enjoyment, computer anxiety, and self-efficacy as antecedents of perceived usefulness and perceived ease of use.

Artificial Intelligence in Education

In the field of AI in education, Zawacki-Richter et al. (2019) conducted a systematic literature review, identifying promising applications in areas such as intelligent tutoring and automated assessment. However, they also pointed out the need for more empirical research on the use of these technologies in higher education. Similarly, Zhi & Wang (2024) express a favourable attitude of EFL learners towards AI to enhance language learning.

The state of the art provides an overview of the various applications, benefits and challenges of AI in education. From personalisation of learning to automated assessment, AI is transforming the educational landscape. However, it also highlights important ethical and practical considerations that must be addressed for a successful and responsible implementation of AI in education:

1. Personalisation of Learning: AI systems are being developed to tailor the content, pace and approach to learning to the individual needs of each learner. Luckin et al. (2016) argue that this personalisation can significantly improve learning outcomes by providing more relevant and effective educational experiences. Recent studies in the period 2020-2025 indicate that generative AI has revolutionized the creation of educational materials, enabling the automated generation of adaptive and personalized content tailored to individual learning needs (Romani Pillpe et al., 2025).
2. Intelligent tutoring systems: Intelligent tutors use AI to provide immediate feedback and personalised support to students. VanLehn (2011) states that these systems can be as effective as tutoring by a human, giving value to guided practice and immediate feedback. Bravo Ortega (2025), in a systematic review of the period 2021-2025, identified that AI-based platforms provide more accurate and contextualized feedback, while freeing teachers from routine tasks.
3. Predicting academic performance: Advanced learning analytics algorithms represent another significant growth area in the application of AI. Siemens (2013) highlights how AI is improving the ability to analyze student progress in real time, enabling more timely and effective interventions. These tools can predict future student performance, identify learning patterns and provide valuable insights for educators. Furthermore, Luan & Tsai (2021) indicate that these models can accurately identify students at risk of academic failure, allowing for early interventions and personalised support; while a systematic review of the literature in 2020-205 determined that AI applications improve educational outcomes by offering the possibility of massive processing of academic data (Modesto Acosta et al., 2024).
4. Continuous and adaptive assessment: AI is also transforming assessment methods in education, adjusting learning content and practices in real time to the level of knowledge demonstrated by the learner, based on the results of student learning analysis (Cuenca Aguilar, 2022).
5. Virtual Assistants in Education: Goel & Polepeddi (2018) analyzed the use of AI-based virtual assistants in higher education. Their case study on Jill Watson, a virtual teaching assistant used at the Georgia Institute of Technology, demonstrated that AI chatbots can effectively handle student queries, freeing up time for human instructors to focus on more complex tasks. Similarly Luna Fox & Paredes Rosado (2024)

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identified studies in 2020-205 that favor their use as 24/7 academic support tools to address student queries.

6. AI and Accessibility in Education: Drigas & Ioannidou (2012) explored how AI can improve accessibility in education for students with disabilities. Their review highlighted the application of AI tools, such as intelligent tutoring systems, for students with dyslexia, dysgraphia and dyscalculia and augmentative communication tools for students with speech disorders. Likewise, Ruiz Muñoz et al. (2025) detected a notable advance in the use of technology to improve cultural and linguistic adaptations to the local environment.
7. Ethics and Privacy in Educational AI: Zawacki-Richter et al. (2019) and Idowu (2024) conducted a systematic review of the literature on AI in higher education, focusing on ethical and privacy implications. They identified key concerns, such as student data protection and transparency in algorithmic decision-making, highlighting the need for clear policies and guidelines for the ethical use of AI in education. Holmes et al. (2019) raised concerns about confidentiality and the ethical use of mass collection and analysis of students' personal data by AI systems.
8. Teacher literacy. In their systematic review corresponding to the period 2020-2025 Luna Fox & Paredes Rosado (2024) determined that teacher training in advanced digital competencies persists as one of the significant challenges in the use of these technologies.

Digital Pedagogy and Educational Transformation

Digital pedagogy and educational transformation represent an emerging paradigm that redefines teaching and learning processes in 21st-century higher education, characterized by the critical and strategic integration of digital technologies that transcend the mere instrumental use of technological tools (Sancho-Gil et al., 2020). This transformation involves a profound reconceptualization of the roles of teachers and students, promoting active, collaborative, and personalized methodologies that respond to the demands of a digitalized society (Almenara & Gimeno, 2019). This transformation requires not only adequate technological infrastructure, but also an institutional cultural change that favors pedagogical innovation and the development of critical digital skills, positioning higher education institutions as active agents in the construction of sustainable and equitable digital educational ecosystems (Bond et al., 2018; García-Peñalvo, 2021). This transformation and digital pedagogy implies:

1. Emerging Conceptual Frameworks. Digital pedagogy has undergone rapid transformation during the period 2020-2025, initially driven by the need to respond to the health emergency and subsequently consolidated as a technology-based educational model (Coreas-Flores & Romero-Argueta, 2024). The transformation of remote teaching due to the emergency (2020-2021) towards structured digital pedagogical models (Pozo et al., 2024) marked a milestone in higher education, setting new standards for technological integration in teaching-learning processes.
2. Consolidation of Hybrid Models. The period 2022-2023 was characterized by the consolidation of hybrid educational models with a multimodal approach, combining digital resources in enriched experiences that favor different learning styles (Mayorga-Ases et al., 2025). During this stage, the growth of microlearning and microcredentials transformed traditional university education paradigms, promoting modular education through non-linear learning paths and curriculum personalization as part of lifelong learning (Arroyave Villa, 2024).
3. Teacher Digital Competencies. National frameworks for teacher digital competencies were established as a strategic priority, with specific training programs developed for the effective integration of educational technologies (Berrú Torres et al., 2025). The national digital education strategies implemented during this period prioritized institutional transformation and the creation of digital educational ecosystems (Gros Salvat & Cano García, 2021).
4. Integration with AI. Currently (2024-2025), AI-mediated learning experiences represent the frontier of digital pedagogy (Miao & Holmes, 2024), facilitating the creation of adaptive digital collaborative environments and lifelong learning platforms that respond dynamically to the individual and group needs of students, in response to which UNESCO intrinsically requires a human-centered approach to AI. In the context of artificial intelligence, digital pedagogy takes on additional dimensions of complexity by incorporating adaptive systems that enable personalized learning, automated assessment, and immediate feedback, generating new challenges related to technological acceptance, teacher digital competencies, and ethics in the use of educational algorithms (Zawacki-Richter et al., 2019).

Operationalization of variables

1. Dependent variable: Intention to use AI tools
   Indicators: Expected frequency of use, willingness to use AI tools in academic tasks
2. Independent variables:
   a) Perceived usefulness

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Indicators: Perception of improvement in academic performance, efficiency in task completion.

b) Perceived ease of use
   Indicators: Ease of learning, clarity of user interface
c) Understanding of AI technology in education
   Indicators: Perceived benefits, perceived risks

3. External variables:
   a) Previous experience with technology.
      Indicators: Level of familiarity with digital tools, frequency of use of technology in learning.
   b) Institutional support.
      Indicators: Availability of resources, training for teachers and students on the use of AI.
   c) Academic faculty.
      Indicators: Academic faculty, integration of technology into the curriculum.

METHODOLOGY

Research design

A quantitative, cross-sectional, correlational, quantitative research design was used.

Population and sample:

The population consists of students enrolled in a university higher education institution in El Salvador**.** The sample consisted of 190 university students from various academic faculties, selected at convenience based on their availability at the time of data collection.

Instruments

A questionnaire was developed based on validated TAM scales (Al-Adwan et al., 2023; Davis, 1986, 1989) adapted to the specific context of AI tools in higher education. The questionnaire included sections for each study variable, with items measured on a 5-point Likert scale, where 1 is the maximum value of disagreement and 5 the maximum value of agreement, a scale that facilitated quantitative analysis using descriptive and inferential statistics. Section 1 collects essential demographic information, including academic faculty, to allow comparisons between different areas of study; sections 2-3 address the external variables identified in the study (Previous Experience with Technology and Institutional Support), while sections 4-6 represent the core constructs of the TAM (Perceived Usefulness, Perceived Ease of Use, and Intention to Use). Section 7 includes questions identifying the benefits perceived by students regarding the use of AI in education. Finally, section 8 seeks to identify the risks perceived by students arising from the implementation of AI in their academic training.

Procedure

The questionnaire was administered online via the QuestionPro platform. It was previously validated by experts and informed consent was obtained from participants prior to data collection.

Data analysis

The information collected in the survey was exported to a database for processing using Perfect Statistical Professional Presented (PSPP) statistical software. The reliability of the questionnaire, shown in Table 1, was determined using the internal consistency method based on Cronbach's alpha, which measured the degree of internal correlation between the 34 non-demographic items, achieving a result of ,94, which is very high (Palella Stracuzzi & Martins Pestana, 2012, p. 169).

Table 1: *Internal consistency of the instrument*

Variable	**Cronbach's alpha**	**Number of elements**
Previous experience with technology	,82	4
Institutional Support	,82	5
Perceived Usefulness	,92	5
Perceived Ease of Use	,86	5
Intention to Use	,91	4
Perceived Benefits	,90	5
Perceived Risks	,86	6

Descriptive statistics were used to calculate the mean response for each study variable and position it as the students' perception of it. These data can be reviewed in Table 2.

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In this sense, *previous experience with technology* was calculated by obtaining the mean of the Likert scale responses in the questions associated with the variable; it was then classified as follows: 1 to 2 = *With low previous experience,* 3 = *With intermediate experience*, 4 to 5 = *With high previous experience*.

For the variable *Intention to use AI tools*, the mean was calculated and classified as follows: 1 to 2 = *Low intention to use AI tools,* 3 = *Medium intention to use AI tools,* and 4 to 5 = *High intention to use AI tools*.

For the variable *Perceived usefulness*, the mean was calculated and categorized as follows: 1 to 2 = *Low usefulness*, 3 = *Medium usefulness*, and 4 to 5 = *High usefulness.*

Ease of use was calculated as follows: 1 to 2 = *Difficult to use*, 3 = *Moderate ease of use*, 4 to 5 = *Easy to use*.

Institutional support was calculated as follows: 1 to 3 = *No institutional support*, 4 to 5 = *Institutional support*.

To measure *Perceived Benefits*, the mean was calculated and classified as follows: 1 to 2 = *Low perception of Benefits* when using AI tools, 3 = *Medium perception of Benefits* when using AI tools, and 4 to 5 = *High intention of Benefits* when using AI tools.

Finally, to measure *Perceived Risks*, the mean was calculated and categorized as follows: 1 to 2 = *low perceived risk* when using AI tools, 3 = *medium perceived risk* when using AI tools, and 4 to 5 = *high perceived risk* when using AI tools.

FINDINGS

Correlational analyses using Spearman's coefficient revealed that the central constructs of the Technology Acceptance Model (perceived usefulness and ease of use) maintain significant positive relationships with the intention to use artificial intelligence tools in educational contexts, with perceived usefulness being the strongest predictor (Mias, 2018). The results showed that contextual factors such as previous experience with technology and differences between academic faculties had weak associations with the main variables, while institutional support emerged as a moderately influential element, particularly in the perception of usefulness. Additionally, it was confirmed that the intention to use is strongly associated with perceived benefits and weakly associated with risks identified by students, suggesting that the acceptance of AI tools in higher education is mainly determined by the perception of academic value and ease of implementation, with institutional support acting as a facilitator of the technology adoption process.

Table 2 shows the Kolmogorov Smirnov (KS) test, whose results indicate that nonparametric statistical methods should be applied, since the data do not belong to a normal distribution.
Spearman's correlation was calculated to check whether the *intention to use* is related to *perceived usefulness* and *perceived ease of use*, measured according to Mias (2018). See Table 3 and Figure 1.

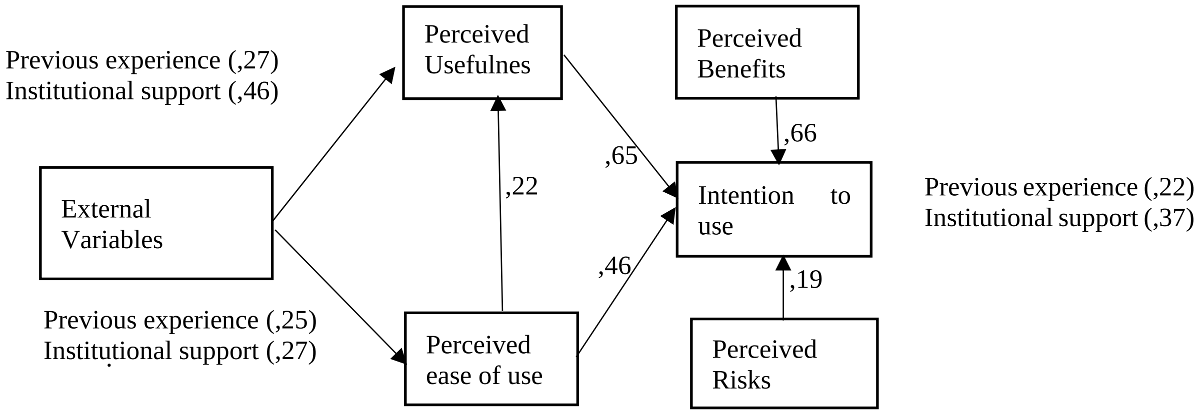

Figure 1: *Technology Acceptance Model*

The correlation between *perceived usefulness* and *intention to use* AI tools (H1) is rho = ,65, which is a *high positive correlation (Mias, 2018)*. This is because students are more willing to adopt AI tools when they perceive them as useful for their academic activities, including significantly improving their academic performance, self-regulating their learning, efficiently solving tasks, and improving the quality of their academic work.

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Table 2: *Descriptive Statistics*

	Previous Experience with Technology	**Perceived Institutional Support**	**Perceived usefulness**	**Intention to Use**	**Ease of Use**	**Benefits Perceived**	**Risks Perceived**
N Valid	190	190	190	190	190	190	190
Lost	0	0	0	0	0	0	0
Low / No	5.8%	38.9%	2.6%	3.2%	5.3%	3.2%	14.2%
Intermediate	15.8%		15.8%	28.9%	28.4%	24.7%	48.9%
High / With	78.4%	61.1%	81.6%	67.9%	66.3%	72.1%	36.8%
Mean	2.73	1.61	2.79	2.65	2.61	2.69	2.23
Standard Error of the Mean	.04	.04	.03	.04	.04	.04	.05
Median	3.00	2.00	3.00	3.00	3.00	3.00	2.00
Mode	With high previous experience	With institutional support	High usefulness	With high intention to use AI tools	Easy to use	High perception of benefits of using AI tools	Medium perceived risk when using AI tools
Std Dev	.56	.49	.47	.54	.59	.53	.68
Variance	.32	.24	.22	.29	.34	.28	.46
Curtosis	2.79	-1.81	4.09	.50	.52	1.22	-.84
Asymmetry	-1.96	-.46	-2.17	-1.22	-1.23	-1.46	-.31
Interval	2.00	1.00	2.00	2.00	2.00	2.00	2.00
Minimum	With low previous experience	No institutional support	Low usefulness	With low intention to use AI tools	Difficult to use	Low perception of benefits of using AI tools	Low perceived risk when using AI tools
Maximum	With high previous experience	With institutional support	High usefulness	With high intention to use AI tools	Easy to use	High perception of benefits of using AI tools	High perceived risk when using AI tools
Kolmogorov-Smirnov Z	6.49	5.48	6.74	5.81	5.65	6.10	3.61
Asymptotic Significance (2 tails)	.000	.000	.000	.000	.000	.000	.000

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Table 3: *Spearman's Correlation*

Factors	Intention of use of AI tools	Perceived usefulness	Ease of use
Perceived usefulness	,65		
Perceived ease of use	,46	,40	
Previous experience with technology	,22	,27	,25
Institutional support	,37	,46	,27
Perceived benefits	,66	,51	,40
Perceived risks	,19	,14	,21

Regarding the correlation between *perceived ease of use* and *intention to use* AI tools (H2) is rho = .46, which is considered a *moderate positive correlation,* which indicates that, while important, it is not as crucial as *perceived usefulness*.

Statistical tests show that *previous experience with technology* and *institutional support* are external variables to the TAM model that show a correlation as follows:

Previous experience with technology has a *low positive correlation* with *perceived usefulness* (rho=,27), *ease of use* (rho=,25), and *intention to use* (rho=,22) of AI tools in education; while *institutional support* shows a *low correlation* with *intention to use* (rho=,37) and *ease of use* (rho=,27), but a *moderate correlation* with *perceived usefulness* (rho=,46).

The *low positive correlation* between the *intention to use* AI tools and external variables, such as *previous experience with technology* (rho=,22) and *institutional support* (rho=,37), remains important but not crucial, highlighting the importance of considering contextual factors in the implementation of AI tools in higher education.

These correlations led to the development of H3; a Kruskal-Wallis test was performed to compare the influence of *previous experience with technology* on *perceived usefulness* (X^2=14.72, p<,05), *ease of use* (X^2=11.91, p<,05), and *intention to use* (X^2=9.751, p<,05). This means that the null hypothesis of independence between *previous experience with technology* and the TAM variables cannot be accepted. This influence stems from the fact that students have already had contact with the use of digital technologies applied to education in the last three years, which allows them to feel comfortable exploring new technologies for their learning on their own and using them for their academic activities.

Similarly, the U-Mann Whitney test was applied to compare *institutional support* as a predictor of *perceived usefulness* (U=2724.50, p<,001), *ease of use* (U=3170, p<,001) and *intention to use* (U=2778, p<,001). This means that the null hypothesis of independence of institutional support cannot be accepted; therefore, AI acceptance behavior depends on *institutional support*. This is because the university provides its students with the necessary resources to learn how to use AI tools and has trained teachers who support them and encourage the use of this technology for learning.

To test H4, the Kruskal-Wallis test was performed to compare the faculty groups with the TAM variables, revealing that there are no significant differences between *academic faculties* and *perceived usefulness* (X^2=9.03, p>,05), *ease of use* (X^2=3.25, p>,05), and *intention to use* (X^2=4.79, p>,05); therefore, the academic faculty is not a determining factor for the perception of the TAM variables. These results coincide with the findings of Zawacki-Richter et al. (2019) and Chen, Xie, et al. (2020), who found in a systematic review that AI is interdisciplinary; that is, it does not affect the perception of the variables in the TAM model. These results confirm that institutional AI implementation strategies can be developed with unified approaches that do not require significant differentiation by faculty, thus optimizing resources and technology adoption efforts.

Continuing with the analysis of the results, a hierarchical regression model was developed to evaluate the moderation of the variables *Previous Experience* and *Institutional Support* with the TAM variables. To do this, the variables were centered by subtracting their respective means to reduce multicollinearity and facilitate interpretation. These centered values were used to create the interaction terms of the TAM variables with the moderating variables.

The hierarchical regression analysis shows that *perceived usefulness* and *ease of use* are robust predictors of the *intention to use* AI tools, while *previous experience with technology* and *institutional support* only become

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relevant when they interact with the main predictors. The final model explains 53% of the variance in the *intention to use*.

The results of the three hierarchical models analyzed to predict the *intention to use* AI tools in higher education are presented in tables 4 - 8.

Table 4: *Hierarchical models of the intention to use AI tools:*

Model	Variables incluided
1	Perceived usefulness, Ease of use
2	Perceived usefulness, Ease of use, Previous experience with technology, Institutional support
3	All of the above + Interactions (Usefulness × Experience, Ease × Experience, Usefulness × Support, Ease × Support)

Table 5: *Model Adjustment Statistics*

Model	R	R^2	Adjusted R^2	Standar Error	F (df)	p
1	.70	.48	.48	.39	87.49 (2,187)	<.001
2	.70	.49	.48	.39	44.49 (4,185)	<.001
3	.73	.53	.51	.38	25.38 (8,181)	<.001

The final model (Model 3) explains 53% of the variance in intention to use, showing a substantial improvement by including interaction terms.

Regression Coefficients and Significance

Table 6: *Model 1: Main predictors*

Variable	B	Std. Error	Beta	t	p
(Constant)	.29	.18	.00	1.60	.111
Perceived usefulness	.65	.07	.56	9.55	<.001
Ease of use	.21	.05	.23	3.88	<.001

Table 7: *Model 2: Adding external variables*

Variable	B	Std. Error	Beta	t	p
(Constant)	.23	.20	.00	1.16	.249
Perceived usefulness	.60	.08	.52	7.85	<.001
Ease of use	.20	.05	.22	3.73	<.001
Previous experience with technology	.03	.05	.03	0.48	.632
Perceived institutional support	.10	.07	.09	1.47	.143

Table 8: *Modelo 3: Including interactions*

Variable	B	Std. Error	Beta	t	p
(Constant)	-.23	.32	.00	-.72	.474
Perceived usefulness	.73	.11	.63	6.39	<.001
Ease of use	.23	.05	.25	4.30	<.001
Previous experience with technology	.05	.06	.05	0.83	.406
Perceived institutional support	.05	.07	.05	0.82	.413
Interaction between usefulness and previous experience	.35	.11	.31	3.25	.001
Interaction between ease of use and previous experience	.28	.11	.22	2.51	.013
Interaction between usefulness and institutional support	.22	.20	.10	1.08	.281
Interaction between ease of use and institutional support	.15	.11	.08	1.33	.185

The results present the model with the variables P*revious Experience in Technology* and *Institutional Support* as moderators of the TAM variables, finding that:

- *Perceived usefulness* and *ease of use* are significant and consistent predictors of *intention to use* across all models ($p < .001$).
- *Previous experience in technology* and *institutional support* are not significant direct predictors ($p > .05$), but their interactions with the main predictors are:

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- The *Utility* × *Previous Experience* (β = .31, p = .001) and *Ease* × *Previous Experience* (β = .22, p = .013) interactions are significant, indicating that the effect of *utility* and *ease of use* on intention to use is stronger in students with greater *technological experience*.
- Interactions with *institutional support* do not reach statistical significance.

- The final model (Model 3) increases the explained variance ($R^2 = .53$), demonstrating the importance of considering moderating effects.

CONCLUSIONS

The results of this research provide solid empirical evidence that should guide change in organizational culture toward pedagogical innovation as an institutional value, the development of specific pedagogical policies and strategies to maximize the successful adoption of artificial intelligence tools in the university context.

The *high* correlation between *intention to use* and *perceived usefulness* (rho = .65) and the *moderate* correlation with *ease of use* (rho = .46) reveal patterns of acceptance that require structured and differentiated institutional responses. This finding (rho = .65) is in line with previous research and instrument validation on the adoption of educational technologies (Chen, Zou, et al., 2020; Gálvez-Marquina et al., 2024; Scherer et al., 2019) and recent meta-analyses confirming a high relationship between TAM variables and the acceptance and adoption of educational AI tools (Ali et al., 2024); while rho = .46 is because students are willing to put effort into learning how to use AI tools if they perceive the potential usefulness is positive and moderate, which is close to the results obtained by Navarro et al. (2023) compared with a rho = ,56 and Criollo-C et al. (2023) who identified that students consider that emerging technologies are directly proportional to their academic performance so they are willing to learn to use them.

These findings can be considered when formulating strategies for more effective implementation of AI in higher education, thus contributing to the evolution of teaching and learning methods in the digital age.

1. The variables of the Technology Acceptance Model (TAM) are *positively related* to university students' acceptance of the use of AI tools in education.
2. The external variables of *previous experience with technology* and *institutional support are positively related* to the TAM variables, and are also predictors of the acceptance of AI in university higher education.
3. The academic faculties of the participating students do not affect the acceptance of AI tools in university higher education given their transversality, validating the universal applicability of the TAM for AI tools regardless of the specific field of study.

These findings are consistent with other studies that emphasize the importance of context in the adoption of educational technologies (Holmes et al., 2019, p. 161), suggesting that the type and quality of previous experience modulates its influence on intention to use. Criollo-C et al. (2023) found that technological familiarity acquired during 2020-2023 acts as a catalyst for the adoption of new educational technologies. The phenomenon has been conceptualized by Morocho Pintag et al. (2025, p. 2842) as *fostering AI skills* "essential for maximizing the benefits of AI and digitization in society, promoting their adoption in a responsible and equitable manner".

As for institutional support, recent studies demonstrate its critical role as an enabler of adoption. Khushalani (2025) reported that institutions that provide proactive academic support enhance human-centered services. Recent empirical evidence consistently supports these findings. Coreas-Flores & Romero-Argueta (2024) found that students perceive virtual learning environments that institutionally support their academic processes as useful. For its part, the group on artificial intelligence in higher education at the Diálogo Interamericano (2025) identified that higher education institutions have implemented good practices to ensure the adoption of AI, including: curriculum adaptation, adjustments to their assessment strategies, teacher training, and student support (face-to-face tutoring, expanded access to devices and resources, and partnerships to reduce the digital divide).

Higher education institutions should develop implementation policies that recognize the differential importance of the factors identified in this study. The predominance of *perceived usefulness* as the main predictor suggests that institutional policies should prioritize clear and tangible demonstration of the academic benefits of AI tools over ease of use. This implies establishing impact assessment frameworks that document improvements in academic performance, learning efficiency, and the quality of student work.

Evidence on the influence of *institutional support* on *perceived usefulness* (rho = .46) calls for the establishment of regulatory frameworks that not only authorize the use of AI but also actively promote its responsible adoption. Policies should include clear protocols for student data protection, algorithmic transparency, and equity in

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technological access. In addition, it is essential to establish educational AI ethics committees to oversee implementation and continuously evaluate the impact of these technologies on the academic community.

The findings on the dependence of *usefulness* and *ease of use* on *institutional support* justify a budget redistribution that prioritizes investment in educational AI infrastructure. Institutions must allocate specific resources for the acquisition of AI tool licenses, the maintenance of technological infrastructure, and, crucially, the creation of specialized technical-pedagogical support units that act as facilitators of adoption.

This same positive correlation highlights the critical need to develop teacher training programs that go beyond basic technical training. Teachers require specialized training in three areas: technical skills to operate AI tools, pedagogical skills to integrate AI into existing teaching methodologies, and ethical skills to manage the moral and professional implications of using AI in education.

These programs should include practical workshops where teachers can directly experiment with AI tools in simulated teaching contexts, pedagogical innovation labs where they can develop specific applications for their disciplines, and spaces for ethical reflection on the transformative impact of AI on their professional roles.

Institutions should create support ecosystems that include pedagogical innovation centers with staff specialized in educational AI, networks of innovative teachers who share experiences and best practices, priority access to premium AI tools for pedagogical experimentation, institutional time for experimentation and development of AI skills, and academic recognition systems that value pedagogical innovation with AI.

On the other hand, the results regarding students' willingness to invest effort when they perceive usefulness demand training strategies that emphasize concrete academic benefits rather than technical ease. Institutions should develop AI literacy programs that include practical demonstrations of improved academic performance, workshops on specific tasks for each degree program, and peer-to-peer mentoring sessions where students with greater technological experience support their peers.

The evidence of insignificant differences between faculties, contrary to international patterns, suggests a unique opportunity to develop cross-cutting but contextually relevant curriculum integration methodologies. Each faculty should develop specific use cases that demonstrate how AI can solve particular academic problems in their discipline, create interdisciplinary collaborative projects that leverage convergence in attitudes toward AI, and establish pedagogical experimentation labs where students and teachers co-create innovative applications.

The findings on the influence of *prior experience* (low but significant correlations) indicate the need for learning paths that take into account varying levels of technological competence. Institutions should implement digital skills assessment systems upon admission, technology leveling programs for students with less experience, specialized tutorials in educational AI available throughout the academic cycle, and physical and virtual spaces dedicated to experimentation with AI tools.

Regarding the implementation of these initiatives, empirical evidence suggests a phased approach that begins with pilot projects in areas of greatest receptivity, continues with gradual expansion based on evidence of success, and includes ongoing evaluation of the impact on TAM variables. Each phase should include feedback mechanisms that allow for real-time adjustments, rigorous documentation of best practices, and systematization of lessons learned for replication in other areas.

The *intention to use* AI tools among university students is mainly determined by *perceived usefulness* and *ease of use*. However, these effects are significantly enhanced in students with greater *prior experience* in technology, suggesting the need for differentiated training and support strategies. Institutional support, although relevant in the literature, did not show significant direct or moderating effects in this model.

The results of the hierarchical regression model confirm the centrality of *perceived usefulness* and *ease of use* as predictors of the *intention to use* AI tools, with significant moderating effects of prior experience with technology.

The hierarchical model analyzed shows that *perceived usefulness* and *ease of use* are the most robust predictors of AI *usage intention*, explaining up to 53% of the variance ($R^2 = .53$). These results are consistent with international findings:
In the present study, *perceived usefulness* and *ease of use* are found to be the main predictors of *intention to use*. The hierarchical model analyzed shows that *perceived usefulness* ($\beta = .63–.56$) and *ease of use* ($\beta = .25–.23$) are the most robust predictors of AI *usage intention*, explaining up to 53% of the variance ($R^2 = .53$). These results

are above the values reported in meta-analyses and systematic reviews on TAM in educational AI contexts, where *perceived usefulness* has a coefficient of $\beta = 0.374$, while *ease of use* does not have a significant impact (Vivanco Enriquez et al., 2025). The variance explained by the model is also above $R^2 = 0.435$ reported internationally by Torres Nabel & Basilio Rizo (2025), which reinforces the validity and robustness of the results obtained.

Although *prior experience* with technology did not show a significant direct effect on *intention to use*, relevant moderating effects were identified: the interaction between *perceived usefulness* and *prior experience* ($\beta = .31$, $p = .001$), and between *ease of use* and *prior experience* ($\beta = .22$, $p = .013$) were significant. This indicates that the impact of the main TAM predictors is stronger in students with greater technological experience.

These findings are consistent with recent research that has incorporated moderation analysis and multivariate models, which shows that prior experience amplifies the relationship between *usefulness/ease of use* and *intention to use* (Acosta-Enriquez et al., 2024). Similarly, they have reported that students with less *prior experience* with technology have higher expectations of effort in relation to their *intention to use* AI in higher education. For their part, Choudhary et al. (2025) identified that students in technical careers, who by their nature have more experience with the use of technology, show more favorable attitudes toward the adoption of AI in higher education.

In contrast to some of the literature, *institutional support* did not show any significant direct or moderating effects on the *intention to use* in the model analyzed. Although the literature recognizes *institutional support* as a key facilitator for AI adoption (García-Peñalvo, 2021; Zawacki-Richter et al., 2019), several recent studies have found that its impact is mainly manifested through improved perceptions of *usefulness* and *ease of use*, rather than as a direct predictor of *intention to use*, as expressed by Zhao et al. (2025), who identified that *institutional support* improves *ease of use* ($\beta = 0.288$, $p < 0.001$) and *perceived usefulness* ($\beta = 0.179$, $p < 0.001$). The findings of Zhao et al. (2025) explain 47.8% of the variance in student attitude ($R2 = 0.478$) and 59.5% in *intention to use* ($R2 = 0.595$). *Institutional support* in the form of resources, training, and encouragement is essential to bridge the gap between students' technical skills and technology adoption by leveraging *institutional support* infrastructure (Sova et al., 2024). This suggests that *institutional support* should be operationalized in a more specific and visible way to directly influence *adoption intent*. This implies that universities can offer training and instruction among students, fostering environments in which they feel confident to learn and use AI tools like any other technological support in the classroom (Ifenthaler & Schweinbenz, 2013).

In summary, the results of this research provide a solid empirical basis for the development of institutional strategies that not only promote the initial adoption of AI tools but also ensure their sustainable and scalable integration into the educational ecosystem. Evidence on the importance of students' prior experience in using technology and institutional support as moderators of intention to use based on perceived usefulness and ease of use offers higher education institutions an evidence-based roadmap for successfully addressing educational digital transformation, positioning them as leaders in the responsible and innovative integration of artificial intelligence in 21st-century higher education.

For future research, it is recommended:

- Explore the acceptance of AI tools in different cultural and geographical contexts.
- Investigate the long-term impact of AI tool use on learning outcomes.
- Examine the ethical and privacy implications of using AI in higher education.

Limitations

This study has several limitations that should be considered when interpreting the results. First, the cross-sectional design used prevents establishing causal relationships between the variables of the Technology Acceptance Model and the adoption of AI tools. The sample was limited to students from a specific geographic region of El Salvador, which significantly restricts the generalization of the findings.

Generalization beyond the Salvadoran context faces particular challenges due to cultural differences, technological infrastructure, and educational systems that characterize developing countries. Cultural factors may moderate the relationships proposed by TAM, especially in societies with different individualistic/collectivist values and levels of trust in technology. In addition, digital divides and varying degrees of digital literacy prevalent in the region limit the direct transferability of these results to contexts with different levels of technological development.

The exclusive use of self-report measures is another significant limitation. These instruments are susceptible to social desirability bias, personal presentation, and memory errors when recalling previous interactions, which can

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distort reported perceptions of the *usefulness* and *ease of use* of AI tools. Self-report measures often overestimate actual technology use and show weak correlations with objective performance assessments.

It is recommended that future research incorporate longitudinal designs, diversify samples geographically and culturally, and triangulate self-report data with objective measures of technology use to improve the validity and generalizability of findings.

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