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Modeling of the adoption of artificial intelligence tools in higher education: a TAM -based approach

Modelado de la adopción de herramientas de inteligencia artificial en la educación superior: un enfoque basado en TAM

Modelagem da adoção de ferramentas de inteligência artificial no ensino superior: uma abordagem baseada em TAM

Abstract

Introduction: artificial intelligence (AI) has emerged as one of the most transformative technologies in higher education, providing tools that facilitate personalized learning and optimize academic and administrative processes; however, its adoption depends on individual and organizational factors. **Objective:** to analyze the influence of perceived usefulness, ease of use, attitude, and intention to use on the adoption of AI tools among university students through the Technology Acceptance Model (TAM). **Method:** a quantitative descriptive-correlational approach was employed, applying a validated questionnaire to 55 students with prior experience in AI, and the data were processed using Pearson correlations and multiple regression analysis. **Results:** intention to use was identified as the most relevant predictor of actual use ($β = 0.679$, $p < 0.001$), followed by perceived usefulness ($β = 0.374$, $p = 0.024$), while ease of use had no significant impact, and attitude showed an inconclusive negative relationship. **Conclusion:** the TAM model proved pertinent in explaining the adoption of AI tools in higher education, highlighting that perceived usefulness and intention to use are the determining factors to ensure effective implementation of these technologies.

Keywords: artificial intelligence, higher education, technology adoption, perceived usefulness

Resumen

Introducción: la inteligencia artificial (IA) se ha consolidado como una de las tecnologías más transformadoras en la educación superior, al ofrecer herramientas que facilitan la personalización del aprendizaje y optimizan los procesos académicos y administrativos; sin embargo, su adopción depende de factores individuales y organizacionales.

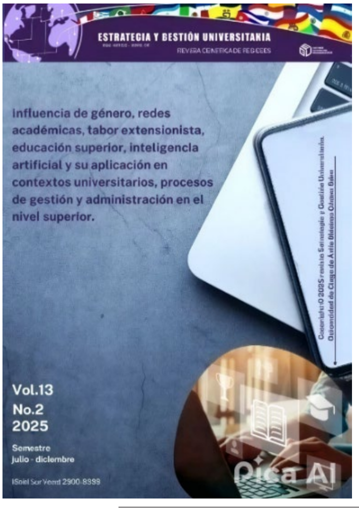
Objetivo: analizar la influencia de la utilidad percibida, la facilidad de uso, la actitud e intención de uso en la adopción de herramientas de IA en estudiantes universitarios mediante el Modelo de Aceptación Tecnológica (TAM). **Método:** se empleó un enfoque cuantitativo descriptivo-correlacional, aplicando un cuestionario validado a 55 estudiantes con experiencia previa en IA, y los datos fueron procesados mediante correlaciones de Pearson y regresión múltiple. **Resultados:** la intención de uso se configuró como el predictor más relevante del uso real ($\beta = 0.679$, $p < 0.001$), seguida por la utilidad percibida ($\beta = 0.374$, $p = 0.024$), mientras que la facilidad de uso no tuvo un impacto significativo, y la actitud mostró una relación negativa no concluyente. **Conclusión:** el modelo TAM resultó pertinente para explicar la adopción de herramientas de IA en la educación universitaria, destacando que la utilidad percibida y la intención de uso son los factores determinantes para garantizar una implementación efectiva de estas tecnologías.

Palabras clave: inteligencia artificial, educación superior, adopción tecnológica, utilidad percibida

Resumo

Introdução: a inteligência artificial (IA) consolidou-se como uma das tecnologias mais transformadoras no ensino superior, ao oferecer ferramentas que facilitam a personalização da aprendizagem e otimizam os processos acadêmicos e administrativos; entretanto, sua adoção depende de fatores individuais e organizacionais. **Objetivo:** analisar a influência da utilidade percebida, da facilidade de uso, da atitude e da intenção de uso na adoção de ferramentas de IA por estudantes universitários, por meio do Modelo de Aceitação Tecnológica (TAM). **Método:** foi empregado um enfoque quantitativo descritivo-correlacional, aplicando-se um questionário validado a 55 estudantes com experiência prévia em IA, e os dados foram processados por meio de correlações de Pearson e regressão múltipla. **Resultados:** a intenção de uso configurou-se como o preditor mais relevante do uso real ($\beta = 0.679$, $p < 0.001$), seguida pela utilidade percebida ($\beta = 0.374$, $p = 0.024$), enquanto a facilidade de uso não apresentou impacto significativo, e a atitude mostrou uma relação negativa inconclusiva. **Conclusão:** o modelo TAM mostrou-se pertinente para explicar a adoção de ferramentas de IA na educação superior, destacando que a utilidade percebida e a intenção de uso são os fatores determinantes para garantir uma implementação efetiva dessas tecnologias.

Palavras-chave: inteligência artificial, ensino superior, adoção tecnológica, utilidade percebida



Introduction

Artificial Intelligence (AI) has established itself as one of the most transformative technologies in the educational domain, offering significant opportunities to personalize teaching, optimize administrative processes, and enhance pedagogical decision-making (Galdames, 2024). In the context of higher education, the incorporation of AI-based tools—such as intelligent tutors, automated assessment systems, predictive analysis of student performance, and virtual assistants—has the potential to redefine pedagogical practices, learning environments, and institutional management.

Al Badi et al. (2024) found a positive correlation between the components of the Technology Acceptance Model (TAM) and the factors influencing the use of Microsoft Teams in virtual learning. However, aspects such as technological skill level and years of teaching experience did not show significant differences in faculty perceptions regarding the platform.

The emergence of AI is transforming teaching methods, administrative processes, and learning strategies in the university context (Morales, 2025; Galdames, 2024). Various studies have demonstrated its potential to personalize education, optimize student performance assessment, and enhance institutional efficiency (Contreras & Guerrero, 2025). Nevertheless, despite its growing adoption, gaps remain in understanding the factors that condition its effective implementation by students and educators, especially in contexts characterized by resource limitations or cultural resistances (Widodo et al., 2024).

The most significant challenges identified in the literature lie in the complexities of incorporating AI tools in academic contexts, where perceived utility, usability, and attitudes toward technology are crucial (Davis, 1989; Venkatesh et al., 2003). Research by Kanont et al. (2024) and Zambrano Vera et al. (2024) has examined these variables (perceived usefulness, ease of use, and intention to use), yielding results that differ depending on the context, thereby highlighting the importance of conducting further studies that take into account the specificities of each educational setting. The link between intent to use and actual adoption behavior requires more investigation, as it does not always lead to sustainable implementation (Sergeeva et al., 2025).

The TAM model serves as a reference framework used to forecast the intention and usage of technologies in higher education. Vanduhe et al. (2020) combined the TAM model with social motivation and Task-Technology Fit (TTF) to analyze the intention to continue using gamification in higher education. TAM has been employed to analyze the adoption of various educational technologies, such as Learning Management Systems (LMS) (Fathema et al., 2015), mobile technologies (Buana et al., 2021), e-learning, YouTube as a learning medium (Chintalapati et al., 2017), cloud computing for academic purposes (Amron et al., 2021), and gamification for training (Vanduhe et al., 2020).

The foundations of the TAM model are theoretical and support the process of analyzing technology adoption (Buana et al., 2021). Research frequently employs a pure TAM approach, focusing on usability and ease of use (Chintalapati et al., 2017). Recently, studies have adapted the pure TAM model by adding other relevant external constructs in higher education (Fathema et al., 2015). Linear regression analysis and structural equation modeling (PLS-SEM) are typical strategies for evaluating and validating the TAM model in this area (Amron et al., 2021). Furthermore, the TAM model has been systematically studied to examine its application for understanding the sustainability of higher education, particularly in the context of the COVID-19 pandemic (Rosli et al., 2022).

User perceptions of usefulness (UP) of AI and a growth mindset are crucial elements that impact user attitudes towards technology adoption, serving as essential components in the transition from consideration to active incorporation of AI in various settings (Ibrahim et al., 2025).

The implementation of artificial intelligence (AI) instruments in higher education symbolizes a revolution in pedagogy that demands detailed and organized study. In this context, Mourtajji and Arts-Chiss (2024) indicate that the current exploratory study marks the beginning of a multi-stage research process, starting with an extensive qualitative analysis aimed at educators to refine the conceptual model and understand the professional and personal applications of technologies such as ChatGPT. Subsequently, a quantitative phase focusing on student perceptions and actions is proposed, facilitating comparisons of AI adoption dynamics between educators and students.

This research aimed to provide evidence on how perceptions of usefulness, ease of use, and attitudes influence decisions to integrate AI technologies in the academic sphere. The results contribute to existing literature and offer insights for designing educational policies that promote more effective and equitable adoption of AI in higher education institutions.

Methods and materials

This research adopted a descriptive-correlational quantitative method, focusing on modeling the implementation of artificial intelligence (AI) tools in higher education based on the Technology Acceptance Model (TAM). Sánchez-Prieto et al. (2016) studied how the adoption of mobile technologies in this sector could be understood through the TAM, highlighting its development and the crucial elements determining adoption by educators.

The objective was to examine the perceptions, attitudes, and usage intentions of AI tools among university students, considering five dimensions: perceived usefulness, perceived ease of use, attitude towards use, intention to use, and actual use.

The target population comprised higher education students from technological institutions located in Metropolitan Lima. A non-probabilistic convenience sampling method was employed, selecting students from different majors and academic cycles who had prior exposure to AI tools during their training. The final sample consisted of 55 participants, who voluntarily completed a digital questionnaire.

For data collection, a structured questionnaire was designed, comprising 20 items distributed across the five dimensions of the TAM model adapted to the educational context.

1. Perceived usefulness (4 items): Assesses the extent to which students believe that the use of AI tools enhances their academic performance and facilitates learning.

2. Perceived ease of use (4 items): Measures students' perceptions regarding the simplicity and accessibility of using AI tools in their academic activities.

3. Attitude towards use (3 items): Investigates the overall evaluation that students have regarding the use of AI as support in their education.

4. Intention to use (3 items): Evaluates students' future willingness to continue using AI tools and their readiness to recommend them.

5. Actual use (4 items): Measures the frequency and type of current use of AI tools (such as ChatGPT, Copilot, or Grammarly) in specific academic activities.

Each item was framed as a statement and evaluated using a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree).

To measure the internal consistency of the instrument, the Cronbach's alpha coefficient (α) was determined, resulting in a total value of $\alpha = 0.974$, indicating high reliability across all items.

Data collection took place in the second quarter of 2025, using digital forms that were distributed among student groups. Participation in the survey was ensured to be voluntary and anonymous, thereby respecting ethical principles related to educational research.

The data were processed and analyzed using the Google Colab platform, utilizing the Pingouin library. The pingouin.cronbach_alpha() function was employed to calculate the Cronbach's alpha coefficient and conduct multiple regression analysis. This tool allowed for the assessment of the internal consistency of the questionnaire, both overall and within each dimension of the TAM model.

Results and discussion

The findings derived from the study of the correlations among the constructs of the Technology Acceptance Model (TAM), used in the analysis of the adoption of artificial intelligence (AI) tools in higher education. Table 1 displays the Pearson correlations among the constructs: perceived usefulness (UP), perceived ease of use (PEOU), attitude towards use (ATU), intention to use (IU), and actual use (UB).

Table 1

Correlations among TAM model constructs

	UP	PEOU	ATU	IU	UB
UP	1.00	0.73	0.79	0.77	0.75
PEOU	0.73	1.00	0.63	0.76	0.73
ATU	0.79	0.63	1.00	0.78	0.62
IU	0.77	0.76	0.78	1.00	0.83
UB	0.75	0.73	0.62	0.83	1.00

Source: Authors' own elaboration.

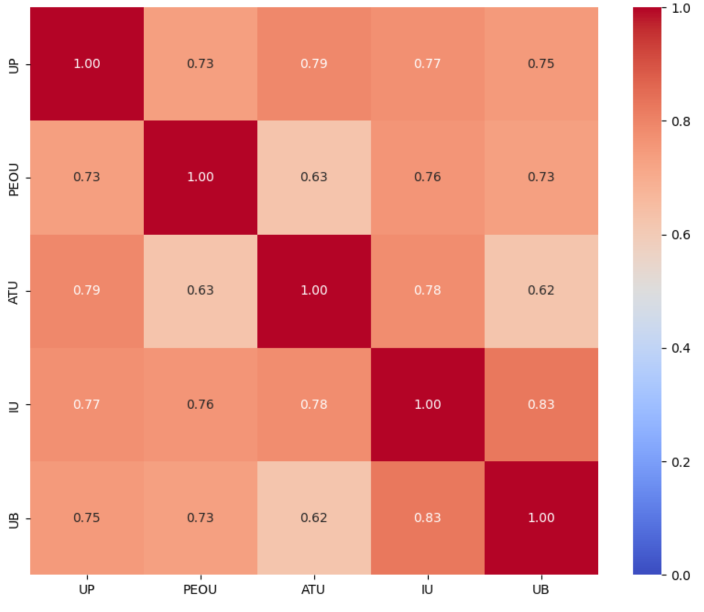
The findings revealed positive and significant connections among all studied constructs. Perceived usefulness (UP) demonstrated a strong correlation with attitude towards use (ATU) ($r = 0.79$), intention to use (IU) ($r = 0.77$), and actual use (UB) ($r = 0.75$), thereby corroborating the main hypothesis of the TAM model regarding how perceived usefulness directly influences technology adoption.

A high correlation was shown between perceived ease of use (PEOU) and intention to use ($r = 0.76$) and actual use ($r = 0.73$), thereby supporting its role as a facilitator of adoption behavior. However, its correlation with attitude towards use ($r = 0.63$) was moderate, indicating that, in this scenario, the perception of ease contributed to a positive disposition, though not decisively.

Finally, intention to use (IU) emerged as the primary predictor of actual use (UB), with a correlation of $r = 0.83$—the highest in the matrix—underscoring its mediating role between initial perceptions (UP, PEOU, ATU) and actual usage behavior. Figure 1 presents the results obtained from the correlation analysis.

Figure 1

Correlations among TAM model constructs applied



Source: Authors' own elaboration.

The results of the multiple linear regression model (Table 2) indicated that, among the analyzed constructs, intention to use (IU) emerged as the most important predictor of actual use of artificial intelligence (AI) tools (UB) in the context of higher education. The standardized coefficient for IU was ß = 0.679, and its p-value was $p < 0.001$, indicating a strong and conclusive positive impact from a statistical perspective.

Similarly, perceived usefulness (UP) was identified as a relevant factor (ß = 0.374, $p = 0.024$), indicating that as students perceive AI tools to add value to their academic tasks, their level of use increases.

Perceived ease of use (PEOU) was not significant ($p = 0.2197$), suggesting that it did not have a direct effect on actual use when controlling for the other factors in this model. This finding could be interpreted as a prioritization of functional advantages over operational advantages in academic environments, where references are more often made to effects on learning or performance.

Meanwhile, attitude towards use (ATU) presented an inversely proportional relationship with actual use (ß = -0.208) but did not reach significance at the 5% level ($p = 0.0992$). This indication revealed some complexity in the relationship between attitudinal tendencies and practical action, which may require considerations from a qualitative research perspective or mediation frameworks.

Table 2

Predictors of AI tools use (UB)

Independent variable	Coefficient (ß)	Standard error	t-value	p-value	95% CI Lower	95% CI Upper
Constant	-0.087	0.362	-0.239	0.8117	-0.814	0.64
Perceived usefulness (UP)	0.37	0.16	2.33	0.02	0.05	0.70
Perceived ease of use (PEOU)	0.17	0.13	1.24	0.22	-0.10	0.43
Attitude towards use (ATU)	-0.21	0.12	-1.68	0.10	-0.46	0.04
Intention to use (IU)	0.68	0.15	4.52	0.00	0.38	0.98

Source: Authors' own elaboration.

Intention to use (IU) was established as the most potent and significant predictor of actual use (UB) of AI tools, consistent with previous research that identifies intention as the best determinant of actual behavior in technological contexts (Davis, 1989; Venkatesh et al., 2003).

Perceived usefulness (PU) also demonstrated a positive and significant impact on actual use, reinforcing the idea that users primarily value the functional benefits these technologies bring to their academic activities. This finding aligns with the literature highlighting perceived usefulness as a key driver in technology adoption, especially in contexts where performance improvement is prioritized (Venkatesh et al., 2003).

These results are consistent with reports by Yong et al. (2010), who observed that the use of ICT increases as students progress through their university education, largely due to curricular demands, especially in technological fields. Additionally, they identified that students with a three-year bachelor's degree tend to use ICT more compared to those with only two years of study. Calle-Díaz et al. (2024) highlighted that perceived usefulness and ease of use directly influence students' willingness to employ technological tools and share academic content. Greater technological acceptance leads to more effective information dissemination, underscoring the importance of promoting platforms perceived as accessible and functional within the educational environment.

In contrast, perceived ease of use (PEOU) was not a significant predictor of actual use when examined alongside the other constructs, although it remained significant in its relationship with intention to use and actual use. This could indicate that, within higher education, ease of use may serve more as an indirect facilitator influencing intention to use rather than directly predicting effective behavior. It can be assumed that students with prior experience or digital skills may not view ease of use as a significant barrier, giving more importance to the advantages than to the convenience of operations.

Research such as that by Ngabiyanto et al. (2021) provided relevant nuances by extending the TAM model, demonstrating that ease of use does not always positively affect adoption intention. In their study, teacher disposition was the most determinant factor, even above perceived usefulness, while ease of use had a negative significant effect on the intention to utilize online learning platforms.

Furthermore, there exists a negative, although not significant, link between attitude towards use (ATU) and actual use, suggesting complexity and heterogeneity in attitudes during the technology adoption process. This result highlights the need for future research to analyze how contextual, emotional, or social factors may mediate this relationship, utilizing qualitative techniques or more sophisticated structural models.

In this context, Al-Abdullatif (2024) expanded the Technology Acceptance Model (TAM) by integrating AI competency, intelligent TPACK, and perceived trust, emphasizing the importance of considering not only individual variables but also organizational and pedagogical factors to more explicitly explain the barriers and facilitators for adoption. He warns against the limitations of using self-reported measures, which may not accurately reflect actual technology use, suggesting that future research should couple these measures with observational data for a more precise view of AI adoption as part of university teaching.

The correlations established among the constructs corroborated the internal consistency of the TAM model in this analysis, reinforcing the idea that initial perceptions impact intention, which in turn affects final behavior. Similarly, Barz et al. (2024) validated the TAM model among university students, highlighting the additionality of self-regulated learning and the inclination towards technology in increasing acceptance of e-learning environments. Although they also considered digital self-efficacy as an external construct, they found no significant effect in its relationship with perceived ease of use or perceived usefulness, evidencing that technology adoption can be a complex process that requires further research.

Limitations and future research directions

The study has limitations related to the small sample size (N = 55), which restricts the stability and generalization of the results. Additionally, the use of a non-probability convenience sampling method limits the external validity of the findings. Although the Cronbach's alpha (α = 0.974) reflects good reliability across the items, it is recommended to refine and validate the instruments in future research. To strengthen the robustness and applicability of the results, it is suggested to increase the sample size, employ probability sampling techniques, and explore new variables.

Conclusions

This study reaffirms the usefulness and validity of the TAM for explaining the implementation of artificial intelligence tools in the context of higher education. It has been determined that Intention to Use (IU) is the most significant predictor of actual use, indicating that motivation and willingness to employ AI are essential elements for the effective implementation of these tools.

Moreover, Perceived Usefulness (PU) also plays an important role by positively influencing actual use, reflecting the fact that individuals using these tools value the practical and functional benefits that AI can provide to their academic activities. In contrast, Perceived Ease of Use (PEOU) has been established as not significant for the direct prediction of actual use, suggesting that in the context of higher education, the simple and successful utilization of these tools may not play as important a role compared to the perception of value in using the corresponding technology.

On the other hand, the attitude towards use demonstrated a negligible negative correlation with actual use, providing evidence that suggests a complex relationship, encouraging its study under complementary methodological approaches.

Thus, educational institutions should prioritize strategies that enhance the perceived usefulness of artificial intelligence through formative practice, promote intention to use via ongoing awareness programs, understand attitudes through qualitative studies to counteract barriers, and monitor technical and organizational aspects that may make adoption more likely. All these guidelines are essential to ensure the effective and sustained use of AI tools in the academic realm.

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Declaration of author responsibility

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