



Factors influencing the use of artificial intelligence in Peruvian university context

Ivan Iraola-Real ^{1,2*}

 0000-0001-6479-8961

Carla Vasquez Cespedes ³

 0000-0001-7944-1375

Roberto Cotrina-Portal ^{1,4}

 0000-0002-8674-3248

¹ Universidad de Ciencias y Humanidades, Lima, PERU

² Instituto de Educação, Universidade de Lisboa, Lisbon, PORTUGAL

³ Unidad de Posgrado de la Facultad de Humanidades y Ciencias Sociales, Universidad de Ciencias y Humanidades, Lima, PERU

⁴ Universidad Nacional Mayor de San Marcos, Lima, PERU

* Corresponding author: ivanr@edu.ulisboa.pt

Citation: Iraola-Real, I., Vasquez Cespedes, C., & Cotrina-Portal, R. (2026). Factors influencing the use of artificial intelligence in Peruvian university context. *Contemporary Educational Technology*, 18(4), Article ep693. <https://doi.org/10.30935/cedtech/19498>

ARTICLE INFO

Received: 3 Jul 2026

Accepted: 16 Sep 2026

ABSTRACT

Artificial intelligence (AI) has made significant advances in education, but ethical debates surrounding its use persist. Given this issue, this article aims to analyze the factors influencing the use of AI among students at a private university in Lima, Peru. Three studies were conducted in this regard. The first study (N = 125) took a qualitative approach and analyzed the category called **"benefits of AI in university education,"** in which students expressed that AI is useful for optimizing their studies and research. However, in the category **"disadvantages of using AI in university education,"** the students recognized that using AI is risky because it generates information without citing authors; furthermore, it undermines autonomous and critical thinking. Being similar to studies in other countries. For these reasons, in the second study (N = 402), a confidence scale toward the use of AI was adapted, demonstrating reliability and confirmatory validity. Finally, in the third study (N = 928), a path analysis showed that digital self-efficacy and virtual educational performance predicted the perception of the benefits of AI, the reasons for not using it, and educational improvement with AI. Digital anxiety then played a mediating role between virtual educational performance and attitudes toward AI.

Keywords: artificial intelligence, higher education, digital self-efficacy, digital anxiety

INTRODUCTION

Artificial intelligence (AI) is already a present reality, reshaping society, education, and science, as well as the ways in which knowledge is generated (Khor et al., 2026; Storozhyk, 2024). Thus, the idea that machines will compete with humans in all areas of intelligence (Turing, 1950) seems to be coming true, generating profound debates and ethical regulations on their use and future possibilities (Keravnos & Eleftheriou, 2026; Morandín-Ahuerma, 2023; Usak, 2024; Uygun, 2026). In this context, November 2022 saw the launch of ChatGPT as a mass-access AI tool (United Nations Educational, Scientific and Cultural Organization, 2024), starting with 152.7 million visits; and by February 2024, 1.67 billion visits were reported (Mortensen, 2024). Thus, gradually, AI in the university context allowed for a better environment for research (Mahmoud, 2025)

This study is part of a project in educational psychology by the authors, carried out at the Universidad de Ciencias y Humanidades.

and collaborative learning. Teachers also adapted teaching strategies to the diversity of students' learning styles (Usak, 2024), which minimized dropout rates and strengthened online learning (Barrett, 2019; Chu et al., 2022; Kuleto et al., 2021; Salas-Pilco & Yang, 2023). Understanding this process involves looking at how people accept new technologies, in terms of usefulness or ease of use (Davis, 1989), and from a perspective that considers performance and expected effort, social influence and facilitating conditions, which can be affected by gender, age, experience with technology and whether using it is voluntary or mandatory (Venkatesh et al., 2003). Thus, these changes necessitate constant updating in response to AI innovations in teaching (Uygun, 2026), and university administrators must provide adequate support for this process (Chu et al., 2022; Wang et al., 2025).

Nevertheless, attention must be paid to the difficulties related to the accuracy of the information provided by AI and the effects on the teacher-student relationship (Farrelly & Baker, 2023; Qing et al., 2026). This requires strengthening AI literacy (courses in curricula), virtual seminars on the effects of AI on education and research, and ethical criteria for the use of AI technologies (Alqahtani et al., 2023; Uygun, 2026). Added to this is the complexity of professionals' acceptance of AI (Nazaretsky et al., 2022; Zhou & Wang, 2026). This will depend on their trust in the AI (Gerlich, 2024). This trust in AI and the factors that predict it are presented as a new field of research. In this regard, it is prudent to consider that there are barriers to the approval and use of AI in university contexts (Almasri, 2024; Uygun, 2026). Likewise, users (students, teachers, administrators, or researchers) develop attitudes and perceptions that need to be described and explained by establishing the factors underlying the use of AI in different scenarios of university education (Acosta-Enriquez, 2024).

Artificial Intelligence in University Education

It is clear that AI is rapidly transforming various areas, such as the health, financial, and education sectors (Gerlich, 2024; Khor et al., 2026). Education is the area in which the impact of AI is most profound, substantially modifying teaching and learning processes (Ayduğ & Altınpulluk, 2025; Khor et al., 2026; Usak, 2024) and the professional identity for teachers (İsmail & Ibrahim, 2025). This is due to the various strategies that can be applied, such as project-based learning, gamification, self-regulated learning, etc. (Dong et al., 2025). It also offers pedagogical opportunities by accelerating assessment processes through automated grading and intelligent tutorial systems (Ayduğ & Altınpulluk, 2025), which lead to better learning outcomes (Dong et al., 2025). Just like in inclusivity supported by technology (Saborío-Taylor & Rojas-Ramírez, 2024). However, despite the possibilities of AI, people's trust and anxiety towards its use remains a limiting factor for its acceptance in society (Gerlich, 2024; Zhou & Wang, 2026). This is especially true in university settings (Klimova & Pikhart, 2025; Liang et al., 2025), where difficulties in its approval in educational processes have been observed (Almasri, 2024).

Nevertheless, AI has been accepted in hybrid learning processes (Wang et al., 2025; Zhou & Wang, 2026). This has also encouraged research into the benefits of AI in postgraduate studies, mainly in doctoral studies (Mahmoud, 2025). For these reasons, AI has had implications for university curriculum planning (Ayed et al., 2025; Klimova & Pikhart, 2025; Liang et al., 2025), being one of several factors influencing the use of AI. For example, another factor is support from university management for the implementation and adaptation of AI (Chu et al., 2022). Thus, this support from the university significantly influences students' acceptance of AI (Wang et al., 2025). It also influences teachers' acceptance through digital literacy processes as a way to avoid fear or anxiety about AI (Ayduğ & Altınpulluk, 2025; Qing et al., 2026; Zhou & Wang, 2026). Furthermore, at the university level, teaching strategies should be developed in accordance with contextual and cultural factors and their relationship with other factors that predispose attitudes toward the use of AI (Ayed et al., 2025). For example, psychological factors that influence the acceptance of AI. This would support the design of institutional policies tailored to specific contexts, as well as the development of teacher training programs aimed at strengthening AI-mediated teaching practices (Flores-Mamani et al., 2026).

Factors Associated with the Use of Artificial Intelligence

Among the various psychological factors associated with the use of AI, it can mention self-efficacy (Zhou & Wang, 2026), emotional commitment (Wang et al., 2025), academic performance (Dong et al., 2025), gender (Venkatesh et al., 2003), future orientation, digital self-efficacy, and predisposition to use AI (Mahmoud, 2025). Furthermore, in academic matters, in university contexts, it has been observed that the application of AI

facilitates learning and performance (Liang et al., 2025). However, as students make frequent use of AI (Khor et al., 2026), effects on educational performance become evident, as well as other associated aspects such as stress levels, concentration, mental health (Klimova & Pikhart, 2025), general anxiety levels (Ayed et al., 2025), and digital anxiety (Ayduğ & Altınpulluk, 2025; Zhou & Wang, 2026). Nevertheless, among the various factors mentioned above, this article focuses on digital self-efficacy and digital anxiety. Digital self-efficacy because it represents confidence in your own abilities to use tech tools (Bellini et al., 2016). Being a factor that makes it easier to accept using AI (Zhou & Wang, 2026). The digital self-efficacy was observed in university students in China (Wang et al., 2025; Zhou & Wang, 2026), Egypt (Mahmoud, 2025), and professionals in Korea (Moon-Yong & Heayon, 2025). As well, one of the most used frameworks for this purpose is the unified theory of acceptance and use of technology model (UTAUT), originally proposed by Venkatesh et al. (2003), which tries to explain the factors that determine users' acceptance and adoption.

Some of these academic and emotional factors can be seen in the positive effects of digital self-efficacy in reducing digital anxiety (Iraola-Real et al., 2023). Digital anxiety shows up when people feel scared or worried about using new digital devices and tech tools (Bellini et al., 2016). In this regard, studies in Peru found that digital anxiety was higher among students in the final years of vocational training (Iraola-Real et al., 2023). In the United Kingdom, it was found that this type of anxiety depends on the degree of understanding of digital technologies (Gerlich, 2024). Furthermore, in Palestine, it was found that digital anxiety was associated with attitudes toward AI (Ayed et al., 2025). Then, in Turkey, it was observed that this type of anxiety is generated by AI itself (Ayduğ & Altınpulluk, 2025). This confirms that this type of anxiety can be a factor that opposes the use of AI (Zhou & Wang, 2026). However, like anxiety, trust is a key factor in the perception of AI neutrality, accuracy, and transparency, as observed in a cross-cultural study with participants from the United States, the United Kingdom, Germany, and Switzerland (Gerlich, 2024).

The Present Study

The impact of AI on university education is growing, continuous, and problematic. For some, it facilitates the management and personalization of student learning (Akinwalere & Ivanov, 2022; Crompton & Burke, 2023; Kuleto et al., 2021; Usak, 2024). For others, however, it is an inevitable change, requiring a rethinking of the relationship between teaching and learning (Bearman et al., 2023), as well as the professional skills needed for a world of work increasingly focused on AI (Akinwalere & Ivanov, 2022). Consequently, it is important to analyze the factors associated with the use of AI (Khor et al., 2026; Venkatesh et al., 2003). Therefore, instruments adapted to the Peruvian university context are required to analyze these factors, which will serve as the basis for decision-making in university management. Nevertheless, the scale that measures trust in the use of AI (Nazaretsky et al., 2022) was originally designed and validated for teachers, and there is a gap in its validity for university students in Latin America and Peru. In addition, it is unknown how this trust relates to other psychological factors such as self-efficacy, digital anxiety and academic performance. Because of this, the present study aims to achieve the following objective to analyze the factors influencing the use of AI among students at a private university in Lima, Peru. In accordance with this objective, three studies were developed, which are detailed below.

Methodological Procedures

To achieve the objective, a sequential explanatory mixed methodology was proposed. Thus, a qualitative study was planned, the findings of which were explained with two quantitative studies (Creswell & Creswell, 2018). The three studies are part of a research project evaluated by the Ethics Committee of the Universidad de Ciencias y Humanidades (Peru) and were approved with CEI act no. 358 with code 308-2025. Then, coordination was made with the authorities of a private university in Lima (Peru) to apply the scales. Likewise, in all three studies, non-probabilistic convenience sampling was used due to the voluntary willingness and accessibility of participants (Samuel & Merkebu, 2026). Thus, the application of the scales took place during class hours. In this way, study 1 was developed according to the qualitative case study approach (Silva et al., 2021). The purpose was to explore university students' attitudes towards the use of AI during their professional training. Then, based on the coding processes, initial conclusions were drawn (Zada & Urquhart, 2026). It was observed that students have both positive and negative attitudes towards using AI. In study 2, based on these findings from the qualitative study, the quantitative phase was developed (Creswell &

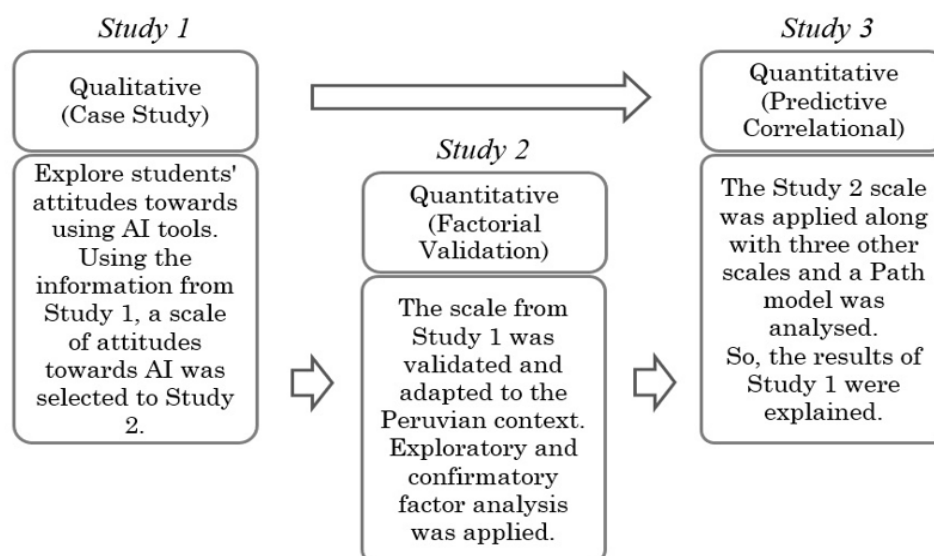


Figure 1. Methodological process of the sequential mixed study conducted (the authors' own elaboration)

Creswell, 2018). Thus, the *“teachers’ trust towards the use of AI scale”* by Nazaretsky et al. (2022) was selected. This scale was adapted to the Peruvian university context and validated through exploratory factor analysis (EFA) (Field, 2018), using the statistical package for social science (SPSS) software (International Business Machines, 2026b). In addition, confirmatory factor analysis (CFA) (Abdelhamid et al., 2024). Additionally, according to the sequential explanatory mixed methodology, study 3 was carried out, applying the validated scale alongside others related to digital self-efficacy, digital anxiety and virtual educational performance. In this way, a path model was developed to predict some predisposing factors for AI use with SPSS Amos software (International Business Machines, 2026a). This path model was assessed according to the fit indices of Hu and Bentler (1999), thus determining the suitability of the predictive results obtained (see [Figure 1](#)).

STUDY 1

In accordance with the proposed objective, an initial qualitative study (Creswell & Creswell, 2018) was conducted, involving case analysis (Silva et al., 2021). This allowed for an exploration of students' perceptions of the benefits and disadvantages of using AI.

Method

Participants and procedures

For this study, the sample consisted of 125 students of both genders, 99 women (79.2%) and 26 men (20.8%), aged between 17 to over 51 years old, studying engineering, health sciences, business economics, as well as humanities and social sciences (see [Table 1](#)). The students responded to an interview guide. The responses were then analyzed using axial and selective coding processes (Zada & Urquhart, 2026) with Atlas ti (2025). Due to the phenomenological and hermeneutic nature of study 1, the AI functions of the Atlas ti (2025) software were omitted. During this process, the validity and reliability of the information obtained was verified using triangulation processes (Fusch et al., 2018). Finally, the data was discussed to gain a better understanding of the use of AI, which guided the methodology of the second and third studies.

Instrument

Participants responded to a semi-structured interview guide (Magaldi & Barler, 2020). This interview was developed based on two categories (*“benefits to the use of AI in university education”* and *“disadvantages of using AI in university education”*). Two questions were adapted from these categories. The first question was: *“In your opinion, are there any other benefits to the use of AI in university education?”* In addition, the second was: *“In your opinion, what are the “disadvantages of using AI in university education?”* Both questions

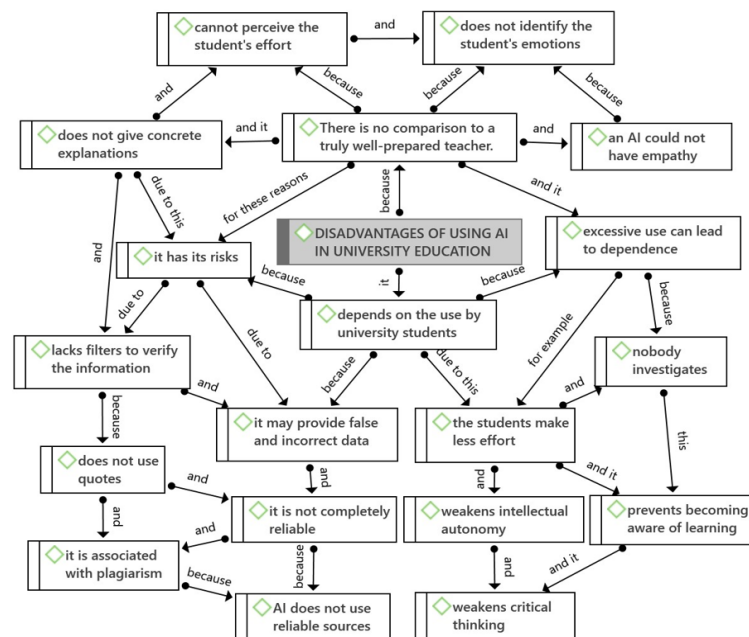


Figure 3. Selective coding of the category “*disadvantages of using AI in university education*” (the authors’ own elaboration)

Benefits of AI in university education: According to this category, the selective coding in [Figure 2](#) shows that, for students, the benefits of AI include those that help improve teaching processes. This confirms studies that support the benefits of AI in university student learning (Klimova & Pikhart, 2025; Liang et al., 2025).

For example, in the studies by Chu et al. (2022; Kuleto et al., 2021) the AI is usefulness in generating learning sessions, making classes more dynamic, and improving understanding of them. These findings can be explained using the TAM model (Davis, 1989), which argues that ease of use and perceived usefulness are the main factors in technology acceptance. In this case, the students also stated that it is beneficial because it recommends individualized methods and exercises. According to Akinwalere and Ivanov (2022; Crompton & Burke, 2023; Khor et al., 2026), these facilitate management and teaching according to each student. This is justified because to Ayduğ and Altınpulluk (2025) AI has the potential to personalize learning. In this sense, the UTAUT model helps us understand that performance expectancy (Venkatesh et al., 2003), understood to the extent to which a student perceives that technology will improve their academic performance, acts as a key factor in positively evaluating these personalized tools.

Another benefit is the optimization of time, the speed of bibliographic searches, and support for the academic writing of abstracts and conclusions. In addition, according to Khor et al. (2026) it is so easy to use and in educational contexts, this has proven to be favorable for research development (Mahmoud, 2025). It is also beneficial for learning languages and mathematics. Confirming the TAM and UTAUT approaches, where the perception of usefulness and functional efficiency of a technology increases students' intention to use it. As general benefits, the students mentioned the reduction of dropouts and student well-being. Nevertheless, the latter results from the association of AI with various psychological aspects such as stress levels or the emotional health of students, which should be investigated (Klimova & Pikhart, 2025) (see [Figure 2](#)). Based on the analysis, it is understood that AI could also have some difficulties that need to be understood (Ayed et al., 2025; Farrelly & Baker, 2023). Therefore, some disadvantages of using AI are analyzed below.

Disadvantages of using AI in university education: For this second category, the analysis of the selective coding in [Figure 3](#) shows some difficulties in the use of AI in university education. For example, the interviewees reflected on the difference between teachers and AI, highlighting that AI cannot be compared to a teacher who is prepared to provide concrete explanations, perceive student effort, and empathize. This reflection leads to questions about the possible replacement of teachers by AI. However, according to Alqahtani et al. (2023; Khor et al., 2026; Qing et al., 2026) AI has been shown to have an impact on the interaction between students and teachers. Nevertheless, from the perspective of the interviewees, AI does not do several things that teachers do. This is an argument that invites us to reconsider how future

Table 2. Demographic data of the sample-2 (age, careers, and term) (n = 402)

Variable	Category	Frequency	Valid percentage (%)
Age range (years old)	17-20	62	38.8
	21-25	30	30.1
	26-30	14	11.7
	31-40	12	13.2
	41-50	5	5.5
	51 years and over	2	.7
Careers	Administration	14	3.5
	Communication and digital media	5	1.2
	Accounting	25	6.2
	Early education	115	28.6
	Primary education	19	4.7
	Nursing	31	7.7
	Pharmacy and biochemistry	87	21.6
	Industrial engineering	39	9.7
	Electronic engineering	1	.2
	Systems engineering	21	5.2
	Nutrition and dietetics	9	2.2
Term of study	Psychology	36	9.0
	First	63	15.7
	Second	65	16.2
	Third	88	21.9
	Fourth	19	4.7
	Fifth	52	12.9
	Sixth	45	11.2
	Seventh	31	7.7
	Eighth	13	3.2
	Ninth	5	1.2
	Tenth	19	4.7
	More than one term	2	.5

interactions will develop during teaching processes (Bearman et al., 2023). Another difficulty observed was related to the unreliability and falsity of the information provided by AI due to its lack of access to reliable sources and failure to cite authors, which associates it with plagiarism. In this sense, Farrelly and Baker (2023) had explained this difficulty, which influences students' levels of trust in AI (Nazaretsky et al., 2022). The most concerning difficulty expressed by the interviewees was the possible dependence on AI, which causes students to read and research less, expressing its negative effects by reducing learning, autonomous thinking, and critical thinking. Which matches the findings of Flores-Mamani et al. (2026). In addition, the interviewees mentioned that the increased use of AI influences emotional states such as frustration at not being able to obtain reliable answers from AI. That according to Ayduğ and Altınpulluk (2025; Zhou & Wang, 2026) this could cause levels of digital anxiety. Or affect academic performance and concentration levels, making further research necessary (Klimova & Pikhart, 2025) (see [Figure 3](#)). Therefore, in the second study, an instrument selected based on the opinions of the students interviewed is validated.

STUDY 2

In the second study, the *“teachers’ trust towards the use of AI scale”* (Nazaretsky et al., 2022) was adapted and validated. This process was carried out using EFA (Field, 2018) and CFA (Abdelhamid et al., 2024) to ensure optimal levels of psychometric validity.

Method

Participants and procedures

The sample consisted of 402 university students, 286 women (71.1%) and 116 men (28.9%), aged between 17 over 51 years old (see [Table 2](#)). The participants responded to an adapted version of the *“teachers’ trust towards the use of AI scale”* (Nazaretsky et al., 2022), which assesses the degree of teacher trust in AI. After selecting the scale, it was translated from English into Latin Spanish. The items were then adapted according

to the students' perspective. This process was carried out using expert judgment (Peker, 2026). After the application, reliability analyses and CFA were performed. In addition, in the CFA (Abdelhamid et al., 2024), the comparative fit index (CFI), goodness of fit index (GFI), adjusted goodness of fit index (AGFI), standardized root mean square residual (SRMR), and root mean square error of approximation (RMSEA) indices were calculated.

Instrument

Students' trust towards the use of AI scale: This scale assesses the degree of trust students have in the use of AI in educational processes. It is an adapted version of the *"teachers' trust towards the use of AI scale"* by Nazaretsky et al. (2022). It has 25 items organized into three dimensions. The first dimension is "perception of the benefits of AI," in which, for example, item 7 proposes: *"Artificial Intelligence can improve teacher professional training, for example using AI-based avatars to simulate and practice teaching scenarios."* The second dimension is "reasons for not trusting AI," in which item 10 states: *"AI algorithms do not understand social, emotional, and motivational factors that are very important in teaching."* And the third dimension is "working with AI for educational improvement," in which item 21 states: *"As they become more prevalent, AI-based tools for personalized learning will gain my full trust."* Each item has five response options ranging from 1 (strongly disagree) to 5 (strongly agree).

Results

Validity and reliability analysis

Initially, reliability was analyzed to verify the consistency of the dimensions and to verify whether all items should be retained. Thus, Cronbach's alpha coefficient was .90 for the overall scale. Then, for the dimension "perception of the benefits of AI," it was .85 (total item correlation: .52-.72); for the dimension "reasons for not trusting AI" it was .79; (total item correlation: .32-.62), and for the dimension "Working with AI for improved pedagogy" it was .91 (total item correlation: .56-.76) (see [Appendix A](#)). Therefore, no items needed to be eliminated. Next, construct validity was studied using EFA the Kaiser-Meyer-Olkin (KMO) sample fit test was .90, with adequate values in Bartlett's sphericity test ($\chi^2 = 4839.143$, $df = 300$, $p < .001$). As well, in the pattern matrix, the factor loadings for items were identified, organized by each of the three dimensions (see [Table 3](#)).

Table 3. Analysis of factors confirming three dimensions (pattern matrix^a)

Items	Components (dimensions)		
	D1	D2	D3
25. I trust the recommendation of an AI-based tool at least as much as that of an expert, like a qualified researcher in their field.	.75		
24. I trust the recommendation of an AI-based tool at least as much as I trust the recommendation of a teacher or classmate.	.74		
17. I totally trust using AI-based custom tools for getting my tasks done.	.73		
22. The more I understand how an AI tool makes decisions, the more confident I will be in it.	.72		
23. The more data available for AI-based tools, the more I can trust the accuracy of their knowledge.	.67		
21. I think that as AI-based tools for personalized learning become more common, I will get more confident using them.	.67		
18. I think I will do well using AI-based tools to personalize my learning when they become available to me.	.59		
20. I think using AI-based tools will change the way I learn a lot.	.59		
19. I think I will use customized AI tools to boost my performance in different classes.	.56		
5. AI can help teachers with management tasks during class.		.71	
2. AI helps me with self-learning in various courses.		.70	
4. AI can help teachers set personalized tasks that suit the students' needs.		.70	
1. AI-based tools help me with tasks like problem solving, writing texts, and making outlines or mind maps, among other things.		.60	
6. AI can help teachers plan their educational activities before class time.		.58	
7. AI can help teachers out, for example, by using AI-based avatars to simulate teaching scenarios.		.55	
3. AI helps me create smart agents (robots or software) that can act as learning buddies.		.44	
15. I think that when AI becomes more common, fewer teachers will be needed.			.41
13. I think there's a lack of transparency in how AI makes decisions to assess students' learning.			.75

Table 3 (Continued).

Items	Components (dimensions)		
	D1	D2	D3
16. I think using data with AI poses risks to students' privacy.			.70
12. I think AI algorithms do not know the student's learning history outside university.			.67
10. I think AI algorithms do not get the social, emotional and motivational factors that are really important in learning.			.66
14. I think AI takes away teachers' autonomy.			.65
8. I think that if there are discrepancies between the evaluation generated by the AI and the teacher's assessment.			.57
11. I think teachers' intuition is better than AI's.			.56
9. I think AI developers lack experience with the reality of university education.			.55

Note. ^aThe rotation has converged in 6 iterations; Extraction method: Principal component analysis; Rotation method: Promax with Kaiser normalization; D1: Working with AI for improved pedagogy; D2: Perception of the benefits of AI; & D3: Reasons for not trusting AI

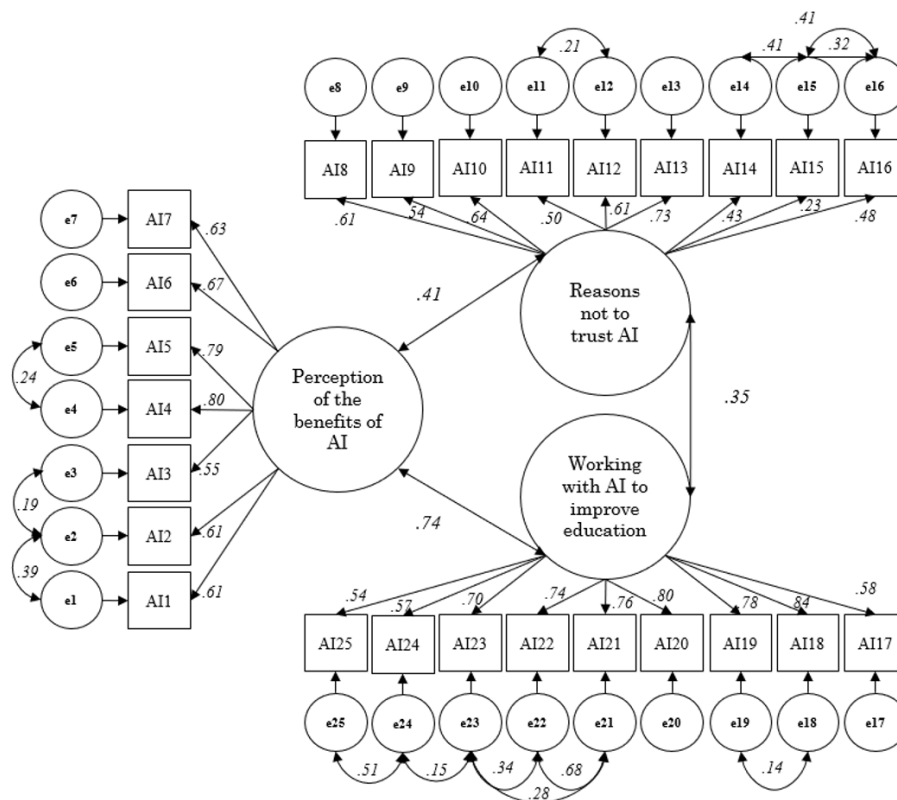


Figure 4. Multifactorial model of the teachers' trust towards the use of AI scale (the authors' own elaboration)

In addition, two models were calculated in the CFA, confirming the three dimensions of the scale (see Figure 4). The first model obtained the following fit indices: $\chi^2(N = 402) = 637.710$, $df = 262$, $p = .000$, GFI = .89, CFI = .92, SRMR = .06 and RMSEA = .06. However, it was not considered because the GFI was not optimal. After correcting the indices and adding some covariances in the second model, it improved, reaching the following values: $\chi^2(N = 402) = 535.522$, $df = 259$, $p = .000$, GFI = .90, CFI = .94, SRMR = .05 and RMSEA = .05.

Discussion

Given the growing impact of AI on management and learning in university education (Crompton & Burke, 2023), this study considered the need to analyze the factors that predict the use of AI. Therefore, an instrument was validated to assess students' attitudes toward AI. Mainly, it evaluates the benefits of AI in student learning (Chu et al., 2002; Kuleto et al., 2021; Usak, 2024), as well as the degree of trust in it (Nazaretsky et al., 2022). In addition, it analyses how AI benefits teaching processes in universities (Barrett, 2019; Salas-Pilco & Yang, 2023). Due to these three considerations, the **"teachers' trust towards the use of AI scale"** by (Nazaretsky et al., 2022) was selected. It was adapted as a version for students called **students' trust towards the use of AI scale**. In this process, the statements of the items for teachers were modified to statements

understandable to university students. Content validity was then assessed by expert judges (Peker, 2026). Although expert agreement was observed, this process was complemented by construct validity using CFA. Adequate levels of validity were achieved in the sample fit test and component extraction (Field, 2018). Additionally, the CFA (Abdelhamid et al., 2024) reaffirmed the validity of the 25-item and confirming the three dimensions. With values confirmed because the CFI value was greater than or equal to .90, RMSEA was between .05 and .09, and SRMR was less than .08 according to the Hu and Bentler (1999) indices.

Then, in the internal consistency analysis, the adapted scale proved to be reliable, both as a general scale and in each of its dimensions. This result was verified for each item, which achieved adequate levels of item correlation because according to Aiken (2002) each item achieved adequate values greater than or equal to .20. Although this adaptation process shows adequate levels of validity and reliability, it is necessary to continue analyzing its psychometric properties with university samples from other contexts. This is logical because, based on this study; it would be the first application of the **students' trust towards the use of AI scale** as an adapted version. Furthermore, if the scale is considered reliable, or could be reliable with lower coefficients (Taber, 2018). Nevertheless, it is necessary to evaluate the number of items. Moreover, while the students are consistent, the possibility cannot be ruled out that some items may be removed for meeting the minimum criteria in their correlation with the total, reducing the level of reliability (Aiken, 2002). This would require a new validation process. Finally, the results are discussed because other reliability analysis processes, such as the test-retest, were not applied; therefore, this is left for consideration in future studies, as shown below.

STUDY 3

The third study aims to analyze the predictive relationship between digital self-efficacy, virtual educational performance, and digital anxiety on attitudes toward the use of AI (perception of the benefits of AI, reasons for not trusting AI, and working with AI for educational improvement). Thus, it aims to identify the predictive variables that influence attitudes toward the use of AI. At the same time, it seeks to confirm the following hypotheses:

- Digital self-efficacy (Moon-Yong & Heayon, 2025), virtual educational performance (Dong et al., 2025), and digital anxiety (Ayed et al., 2025) predict attitudes toward the use of AI (perception of the benefits of AI, reasons for not trusting AI, and working with AI for educational improvement).
- Then, digital anxiety mediates the effects between self-efficacy and virtual educational performance and attitudes toward AI use.

The following methodology was proposed to confirm these hypotheses.

Method

Participants and procedures

The sample consisted of 928 university students studying economics and business, health sciences, engineering, humanities, and social sciences. The students were aged between 17 and 51. A total of 641 (69.1%) women, 275 (29.6%) men, and 12 (1.3%) who reserved the right not to report their gender participated (see Table 4). With regard to ethical criteria, participants responded to four questionnaires after reading an informed consent form (University of Oxford, 2021). Significant relationships between the variables were then analyzed and included in a path model (Awogbemi et al., 2022) with the intention of confirming the hypothesis. Finally, the path model was evaluated according to the criteria of Hu and Bentler (1999).

Instruments

Students' trust towards the use of AI scale adapted version of Nazaretsky et al. (2022). As in the second study, it proved to be valid for the Peruvian context; in the present study, it again achieved optimal values, obtaining a KMO of .92, and Bartlett's test was significant ($\chi^2[N = 928] = 10,276.025$, $df = 300$, $p < .001$). It also showed adequate fit indices: $\chi^2 = 817.628$, $df = 260$, $p = .000$, CFI = .95, GFI = .93, SRMR = .05, and RMSEA = .05. With a Cronbach's alpha of .90 for the overall scale, with .85 for the dimension of "perception of the benefits of AI" (total item correlation = .49-.72); .80 for the second dimension of "reasons for not trusting AI" (total item

Table 4. Demographic data of the sample-3 (age, careers, and term) (n = 928)

Variable	Category	Frequency	Percentage (%)	Valid percentage (%)
Age range (years old)	17-20	445	48.0	48.5
	21-25	254	27.4	27.7
	26-30	97	10.5	10.6
	31-40	89	9.6	9.7
	41-50	26	2.8	2.8
	51 years and over	6	.6	.7
	Missing values	11	1.2	
Careers	Administration	31	3.3	3.4
	Communication and digital media	21	2.3	2.3
	Accounting	32	3.4	3.5
	Law	42	4.5	4.5
	Early education	182	19.6	19.7
	Primary education	50	5.4	5.4
	Nursing	112	12.1	12.1
	Pharmacy and biochemistry	215	23.2	23.3
	Industrial engineering	42	4.5	4.5
	Electronic engineering	1	.1	.1
	Systems engineering	72	7.8	7.8
	Marketing and international business	10	1.1	1.1
	Nutrition and dietetics	11	1.2	1.2
	Psychology	97	10.5	10.5
	Environmental engineering	6	.6	.6
	Missing values	4	.4	
Term of study	First	155	16.7	17.0
	Second	174	18.8	19.1
	Third	136	14.7	14.9
	Fourth	92	9.9	10.1
	Fifth	72	7.8	7.9
	Sixth	146	15.7	16.0
	Seventh	68	7.3	7.4
	Eighth	37	4.0	4.1
	Ninth	6	.6	.7
	Tenth	24	2.6	2.6
	More than one term	3	.3	.3
	Missing values	15	1.6	

Note. Unlike study 1 and study 2, missing values were reported while respecting the voluntary and free choice of the participants; so, we went ahead following the ethical research guidelines

correlation: .37-.61). Moreover, .90 for the third dimension called “working with AI for educational improvement” (total item correlation: .56-.74).

Computer self-efficacy scale adapted version from Bellini et al. (2016). This is a unidimensional scale that assesses the levels of confidence that people have in their abilities to operate technological tools. For the present study, the seven items were translated from English into Spanish. For example, the seventh item states: “*I am curious to explore new technologies that can help me in my university studies.*” Respondents can choose from seven response options: 1 (strongly disagree) to 7 (strongly agree). In this study, its exploratory validity was: KMO = .92, Bartlett’s Sphericity Test was significant ($\chi^2[N = 928] = 4,274.787$, $df = 21$, $p < .001$). With adequate fit indices: $\chi^2 = 91.394$, $df = 11$, $p = .000$, CFI = .98, GFI = .97, SRMR = .02, and RMSEA = .09. The reliability analysis achieved a Cronbach’s alpha of .92 (total item correlation: .69-.82).

Digital anxiety scale adapted from Bellini et al. (2016). This is also a one-dimensional scale that analyses levels of fear and concern about computer tools. The eight items were translated in a similar way. For example, the third item states: “*I feel afraid when faced with new digital technologies in the context of my studies.*” There are seven response options: 1 (strongly disagree) to 7 (strongly agree). For the present study, the exploratory validity was: KMO = .91, Bartlett’s sphericity test was significant ($\chi^2[N = 928] = 4,328.931$, $df = 28$, $p < .001$). In addition, it achieved adequate fit indices: $\chi^2 = 79.153$, $df = 16$, $p = .000$, CFI = .99, GFI = .98, SRMR = .02, and RMSEA = .07. Cronbach’s alpha coefficient was .91 (total item correlation: .63-.80).

Virtual educative performance scale (Iraola-Real et al., 2023) is a self-perception scale of performance using technological resources such as databases or educational platforms. It has five items. For example, the

Table 5. Gender differences

Study variables	Gender	N	Mean	Standard deviation	<i>t</i>	<i>p</i>
Perceived benefit	Male	275	3.66	.80	3.22	.001
	Female	641	3.48	.77	3.16	.002
Reasons not to trust AI	Male	275	3.36	.60	.37	.715
	Female	641	3.34	.68	.38	.701
Working with AI for educational improvement	Male	275	3.43	.76	4.82	.000
	Female	641	3.17	.74	4.78	.000
Digital self-efficacy	Male	275	5.55	1.10	4.45	.000
	Female	641	5.18	1.18	4.58	.000
Digital anxiety	Male	275	3.47	1.44	-3.04	.002
	Female	641	3.78	1.37	-2.99	.003
Virtual educational performance	Male	275	5.02	1.29	2.79	.005
	Female	641	4.78	1.18	2.69	.007

Table 6. Means and correlations

No	Study variables	Mean	Standard deviation	1	2	3	4	5
1	Perceived benefit	3.53	.79					
2	Reasons not to trust AI	3.34	.66	.32***				
3	Working with AI for educational improvement	3.24	.76	.63***	.26***			
4	Digital self-efficacy	5.28	1.18	.44***	.31***	.46***		
5	Digital anxiety	3.69	1.40	.08	.21***	.15***	.03	
6	Virtual educational performance	4.84	1.23	.41***	.30***	.44***	.72***	.15***

Note. The correlations are significant at *** $p < .001$

fifth item states the following: “*Since I have been receiving virtual education, I can perform efficiently in class using technological tools.*” There are seven response options: 1 (strongly disagree) to 7 (strongly agree). For the present study, the exploratory validity was: KMO = .83, Bartlett’s sphericity test was significant ($\chi^2[N = 928] = 1,995.896$, $df = 10$, $p < .001$). With adequate fit indices: $\chi^2 = 23.492$, $df = 4$, $p = .000$, CFI = .99, GFI = .99, SRMR = .02, and RMSEA = .07. Cronbach’s alpha coefficient was .86 (total item correlation: .63-.74).

RESULTS

Analysis of Means and Correlations

In the analysis of mean differences using student’s *t*-test, it was observed that men perceive AI as more beneficial than women ($p < .01$, $t[3.22]$, $M_{men} = 3.66$, $SD_{men} = .80$; $M_{women} = 3.48$, $SD_{women} = .77$). In addition, men reported a greater tendency to think that working with AI leads to educational improvements ($p < .001$, $t[4.82]$, $M_{men} = 3.43$, $SD_{men} = .76$; $M_{women} = 3.17$, $SD_{women} = .74$). Men also reported higher levels of digital self-efficacy ($p < .001$, $t[4.44]$, $M_{men} = 5.55$, $SD_{men} = 1.10$; $M_{women} = 5.18$, $SD_{women} = 1.18$). However, men reported lower levels of digital anxiety ($p < .01$, $t[-3.04]$, $M_{men} = 3.47$, $SD_{men} = 1.44$; $M_{women} = 3.78$, $SD_{women} = 1.37$). Additionally, men reported higher levels of virtual educational performance ($p < .01$, $t[2.79]$, $M_{men} = 5.02$, $SD_{men} = 1.29$; $M_{women} = 4.78$, $SD_{women} = 1.18$). There were no significant differences in the reasons for not trusting AI (see Table 5).

Next, regarding the correlation of variables, digital self-efficacy and virtual educational performance are related to the three dimensions of attitudes toward the use of AI (perception of the benefits of AI, reasons for not trusting AI, and working with AI for educational improvement). In addition, digital anxiety is related to reasons for not trusting AI and the perception that AI influences educational improvement. Finally, digital self-efficacy is related to virtual educational performance, which is related to digital anxiety (see Table 6).

Path Analysis

Next, variables with significant correlations were included in a path model (Awogbemi et al., 2022) (see Figure 5). Based on these results, two models were analyzed. The first model had the following fit indices: $\chi^2(N = 928) = 13.294$, $df = 2$, $p < .01$, CFI = .99, GFI = .99, AGFI = .95, RMSEA = .08, SRMR = .02. However, a non-significant effect was identified between the reasons for distrusting AI and AI for educational improvement. Finally, model 2 showed adequate fit indices: $\chi^2(N = 928) = 13.338$, $df = 3$, $p < .01$, CFI = .99, GFI = .99, AGFI =

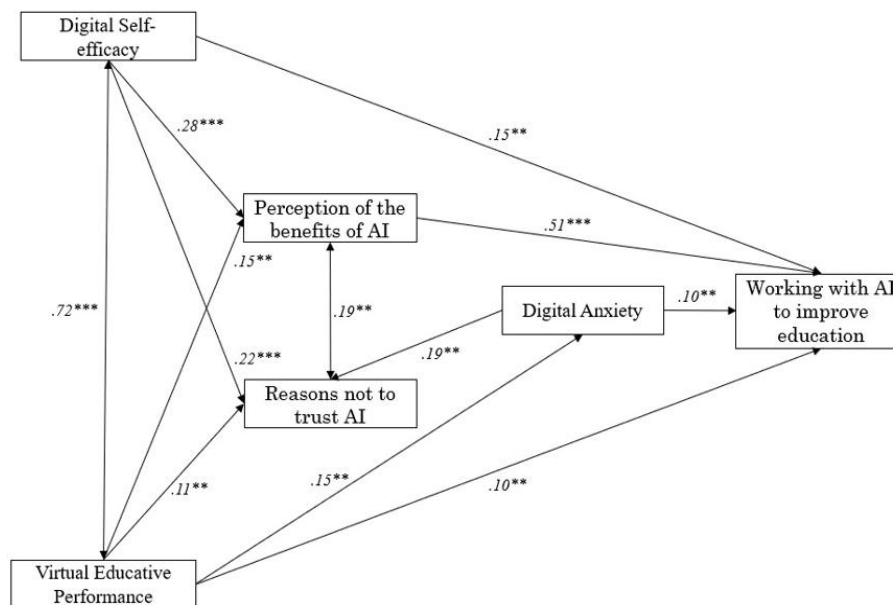


Figure 5. Path hypothesized analysis (the authors' own elaboration)

.97, RMSEA = .06, SRMR = .02. Thus, **Figure 5** shows that digital self-efficacy and virtual educational performance are mutually predictive. Then, digital self-efficacy and virtual educational performance predict the perception that AI is beneficial, that it improves education, but that there are reasons not to use AI. In addition, virtual educational performance predicts digital anxiety. Finally, digital anxiety mediates the effect between virtual educational performance and AI for educational improvement with reasons for not trusting AI.

Discussion

AI influences pedagogical approaches at the university level (Wang et al., 2025). Therefore, it is necessary to understand its innovations and uses in teaching processes (Chu et al., 2022). However, given the controversies surrounding the reliability of AI, its implications for the teaching process (Farrelly & Baker, 2023; Keravnos & Eleftheriou, 2026; Isma'il & Ibrahim, 2025), and the ethical issues associated with its use (Alqahtani et al., 2023; Keravnos & Eleftheriou, 2026; Uygun, 2026). This third study sought to confirm the hypothesis that *digital self-efficacy, virtual educational performance, and digital anxiety predict attitudes toward the use of AI (perception of the benefits of AI, reasons for not trusting AI, and working with AI for educational improvement)*. In particular, it was identified that digital self-efficacy predicts that AI will be perceived as beneficial and will influence educational improvements, but it is possible to distrust it. This is supported by a study of 5,045 professionals in Korea, which found that digital self-efficacy has a moderating effect on the perception of the benefits of AI (Moon-Yong & Heayon, 2025). Furthermore, it is partially confirmed by the studies of Wang et al. (2025; Zhou & Wang, 2026), with university students in China, in whom it was identified that self-efficacy influences the acceptance of AI. It also coincides with the studies by Mahmoud (2025) with 534 graduate students in Egypt. Furthermore, virtual educational performance also predicts attitudes toward the use of AI. This is consistent with systematic reviews of 29 studies in databases such as Scopus, Web of Science, Eric, etc., which showed that academic performance influences the use of AI (chatbots, gamified AI, intelligent tutoring systems, etc.) (Dong et al., 2025).

Although the systematic review does not refer literally to virtual educational performance, but rather to academic performance, the similarity between the two can be inferred because research in learning environments with technological tools was analyzed. This also helps to understand the association between academic performance and AI (Klimova & Pikhart, 2025). The present study confirms that virtual educational performance favors the acceptance of AI. This partially coincides with the studies by Liang et al. (2025), who identify that, in university contexts, educational performance is associated with the application of AI-based technologies. It was then hypothesized that *digital anxiety mediates the effects between self-efficacy and virtual educational performance and attitudes toward the use of AI*. However, this mediating effect of digital anxiety was

only identified between virtual educational performance and the perception that working with AI improves educational processes and the reasons for distrusting AI. Of course, this is related to studies in Palestine, where anxiety was identified as being associated with attitudes toward AI (Ayed et al., 2025). However, this study omits performance. Similarly, in 867 respondents and 53 interviewees in the United Kingdom, anxiety was found to be associated with confidence in using and adopting AI (Gerlich, 2024). In addition, among 221 university teachers in Turkey, moderate levels of anxiety regarding the use of AI were observed, which could be predicted by digital literacy (Ayduğ & Altınpulluk, 2025). Although these studies do not have the same mediating effect, the students allow us to infer that digital anxiety has a certain association with avoiding (Ayed et al., 2025) or using AI in educational processes in various samples (Gerlich, 2024). Based on this, the findings are discussed in terms of the need to expand the results in order to make them more conclusive. Correspondingly, consider studying moderating variables that influence the acceptance of new technologies (Venkatesh et al., 2003), which is acknowledged as a limitation of this study.

GENERAL DISCUSSION

Based on previous studies, it is clear that AI has made significant progress in education (Khor et al., 2026). For these reasons, it was decided to look into how different factors influence the use of AI. Firstly, according to study 1, qualitative analyses show that students recognize AI helps improve the teaching-learning process. Specifically, it helps generate learning sessions, personalize methods and exercises, and optimize the time spent on academic tasks (Chu et al., 2022; Kuleto et al., 2021; Mahmoud, 2025). These perceived benefits can be explained through the TAM (Davis, 1989) and UTAUT (Venkatesh et al., 2003) models, since perceived usefulness and performance expectancy are key factors in positive attitudes towards technology. However, students expressed concerns about the low reliability of information generated by AI, its link to dishonest practices like plagiarism (Farrelly & Baker, 2023). More critically, they highlighted the risks of weakening autonomous and critical thinking (Flores-Mamani et al., 2026). Added to this is the perception that AI cannot replace the human and empathetic dimension of the teaching role. This aligns with views from Luckin et al. (2016), Qing et al. (2026), and Selwyn (2019) who warn of the risk of dehumanizing the educational process when the use of these technologies is not mediated by the teacher. These findings suggest that student acceptance of AI is not one-dimensional but results from weighing its functional benefits against perceived risks regarding reliability, ethics, and educational interaction (Alqahtani et al., 2023; Nazaretsky et al., 2022; Uygun, 2026).

Additionally, regarding study 2, and in response to the need for valid tools to assess these attitudes, the validation of the ***“teachers’ trust towards the use of AI scale”*** (Nazaretsky et al., 2022) as a version aimed at university students provided robust psychometric evidence. Content validity, supported by the judgement of expert evaluators (Peker, 2026), along with favorable results from the EFA and CFA (Abdelhamid et al., 2024), confirm that the scale is valid and reliable for assessing attitudes towards AI in Peruvian university students. In addition, even though the internal consistency values at a general level, in each of its dimensions and items, reinforce the reliability of the instrument according to Aiken (2002). Since this is the first application of this adapted version and a limitation of the current research, it is necessary to continue evaluating its psychometric properties in samples from other university contexts, as well as to complement the analysis with procedures like the test-retest, which were not considered in this phase of the study (Taber, 2018).

According to study 3, these results are consistent with previous research conducted in different cultural contexts, such as the study with Korean professionals that identified a moderating effect of digital self-efficacy on the perception of AI benefits (Moon-Yong & Heayon, 2025). This aligns with the findings of Wang et al. (2025), Zhou and Wang (2026), and with Mahmoud’s (2025) research on university students in China and Egypt. Similarly, the predictive role of virtual educational performance partially matches the systematic review by Dong et al. (2025), which links academic performance with the use of AI-based tools, and the approaches of Liang et al. (2025) in university settings. Regarding the mediating role of digital anxiety, it was only confirmed between virtual educational performance and two of the evaluated attitudes; the perception of educational improvement and reasons for distrust, which aligns with studies conducted in Palestine (Ayed et al., 2025), the United Kingdom (Gerlich, 2024) and Turkey (Ayduğ & Altınpulluk, 2025). These studies also report associations between digital anxiety and attitudes towards technology adoption, though they do not replicate

exactly the same mediation model. While not conclusive, this highlights the need to consider more theoretical approaches and variables related to the use of AI and other technological tools. Finally, this reinforces the idea that adopting AI in higher education does not only depend on the available technological capabilities, but on a mix of cognitive, emotional and contextual factors that need to be considered when designing institutional AI integration strategies (Crompton & Burke, 2023; Wang et al., 2025). Therefore, future research is expected to dive deeper into studying these relationships using longitudinal designs and larger probabilistic samples, which would help strengthen the external validity of the findings reported here.

GENERAL CONCLUSIONS

In short, the identified factorial validity allowed us to recognize the main dimensions that shape university students' attitudes towards AI, including perceived benefits in teaching-learning processes, educational personalization, optimizing academic time, and challenges related to information reliability, technological dependence, as well as the risk of dehumanizing the pedagogical relationship. These dimensions are valid references for measuring AI acceptance in university settings. Likewise, students adopt AI influenced by their digital skills and performance in virtual environments, factors that are linked to digital anxiety, which partly mediates these associations. However, there are concerns about the reliability of the information generated, the lack of source citation and its potential negative impact on critical thinking, highlighting the need for thoughtful use that does not replace human interaction. Consequently, these findings provide an empirical basis for designing institutional strategies that promote ethical and pedagogically effective use of AI, while safeguarding the human dimension of the learning process. Even with some limitations in this research, it helps validate a scale that could be applied to other contexts similar to Peru and provides a theoretical foundation for international bodies overseeing higher education to develop AI use policies and ensure the proper development of professional competences.

Author contributions: **II-R:** conceptualization, formal analysis, writing – original draft; **CVC:** conceptualization, writing – original draft, writing – review & editing; **RC-P:** conceptualization, supervision, writing – review & editing. All authors approved the final version of the article.

Funding: This work was supported by the Unidad de Posgrado de la Facultad de Humanidades y Ciencias Sociales de la Universidad de Ciencias y Humanidades.

Acknowledgments: The authors would like to thank the university students and their professors who made this study possible.

Ethics declaration: This study was approved by the Ethics Commission of the Universidad de Ciencias y Humanidades on 30 October 2025 according to code-308-2025 from the ETHICAL EVALUATION RECORD – CEI no. 358. In the informed consent for the three studies, the participants were told that their involvement was completely anonymous and, as a protective measure, the database is kept strictly confidential.

AI statement: The authors stated that this article was written without using AI tools.

Declaration of interest: The authors declared no competing interest.

Data availability: Data generated or analyzed during this study are available from the authors on request.

REFERENCES

- Abdelhamid, G., Hidalgo, M., French, B., & Gómez-Benito, J. (2024). Partitioning dichotomous items using Mokken scale analysis, exploratory graph analysis and parallel analysis: A Monte Carlo simulation. *Methodology*, 20(3), 187-217. <https://doi.org/10.5964/meth.12503>
- Acosta-Enriquez, B., Farroñan, E., Zapata, L., Garcia, F., Rabanal-León, H., Angaspilco, J., & Bocanegra, J. (2024). Acceptance of artificial intelligence in university contexts: A conceptual analysis based on UTAUT2 theory. *Heliyon*, 10(19), Article e38315. <https://doi.org/10.1016/j.heliyon.2024.e38315>
- Aiken, R. (2002). *Psychological testing and assessment* (11th ed.). Allyn & Bacon.
- Akinwalere, S., & Ivanov, V. (2022). Artificial intelligence in higher education: Challenges and opportunities. *Border Crossing*, 12(1). <https://doi.org/10.33182/bc.v12i1.2015>
- Almasri, F. (2024). Exploring the impact of artificial intelligence in teaching and learning of science: A systematic review of empirical research. *Research in Science Education*, 54, 977-997. <https://doi.org/10.1007/s11165-024-10176-3>

- Alqahtani, T., Badreldin, H. A., Alrashed, M., Alshaya, A. I., Alghamdi, S. S., bin Saleh, K., Alowais, S. A., Alshaya, O. A., Rahman, I., Al Yami, M. S., & Albekairy, A. (2023). The emergent role of artificial intelligence, natural learning processing, and large language models in higher education and research. *Research in Social and Administrative Pharmacy*, 19(8), 1236-1242. <https://doi.org/10.1016/j.sapharm.2023.05.016>
- Atlas ti. (2025). Master your research projects with the power of AI. *Atlas.ti*. <https://atlasti.com/>
- Awogbemi, A., Alagbe, A., & Oloda, S. (2022). On the path analysis techniques and decomposition of correlation coefficients. *Asian Journal of Probability and Statistics*, 20(4), 208-219. <https://doi.org/10.9734/ajpas/2022/v20i4450>
- Ayduğ, D., & Altınpulluk, H. (2025). Are Turkish pre-service teachers worried about AI? A study on AI anxiety and digital literacy. *AI & Society*, 40, 5823-5834. <https://doi.org/10.1007/s00146-025-02348-0>
- Ayed, A., Ejheisheh, A., Al-Amer, R., Aqtam, I., Ali, A., Othman, E., Farajallah, M., Qaddumi, J., & Batran, A. (2025). Insights into the relationship between anxiety and attitudes toward artificial intelligence among nursing students. *BMC Nursing*, 24, Article 812. <https://doi.org/10.1186/s12912-025-03490-2>
- Barrett, M., Branson, L., Carter, S., DeLeon, F., Ellis, J., Gundlach, C., & Lee, D. (2019). Using artificial intelligence to enhance educational opportunities and student services in higher education. *Inquiry: The Journal of the Virginia Community Colleges*, 22(1). <https://commons.vccs.edu/inquiry/vol22/iss1/11>
- Bearman, M., Ryan, J., & Ajjawi, R. (2023). Discourses of artificial intelligence in higher education: A critical literature review. *Higher Education*, 86(2), 369-385. <https://doi.org/10.1007/s10734-022-00937-2>
- Bellini, C., Filho, M., de Moura, P., & Pereira, R. (2016). Self-efficacy and anxiety of digital natives in face of compulsory computer-mediated tasks: A study about digital capabilities and limitations. *Computers in Human Behavior*, 59, 49-57. <https://doi.org/10.1016/j.chb.2016.01.015>
- Chu, H.-C., Hwang, G.-H., Tu, Y.-F., & Yang, K.-H. (2022). Roles and research trends of artificial intelligence in higher education: A systematic review of the top 50 most-cited articles. *Australasian Journal of Educational Technology*, 38(3), 22-42. <https://ajet.org.au/index.php/AJET/article/view/7526>
- Creswell, J., & Creswell, J. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). SAGE.
- Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: The state of the field. *International Journal of Educational Technology in Higher Education*, 20, Article 22. <https://doi.org/10.1186/s41239-023-00392-8>
- Davis, D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319-340. <https://doi.org/10.2307/249008>
- Dong, L., Tang, X., & Wang, X. (2025). Examining the effect of artificial intelligence in relation to students' academic achievement: A meta-analysis. *Computer and Education: Artificial Intelligence*, 4, Article 100400. <https://doi.org/10.1016/j.caeai.2025.100400>
- Farrelly, T., & Baker, N. (2023). Generative artificial intelligence: Implications and considerations for higher education practice. *Education Sciences*, 13(11), Article 1109. <https://doi.org/10.3390/educsci13111109>
- Field, A. (2018). *Discovering statistics using SPSS* (5th ed.). SAGE.
- Flores-Mamani, E., Rojas-Salazar, A. O., Tapia-Espinoza, P.-B., Nieves-Barreto, C.-M., Inquilla-Mamani, J., FloresYapuchura, A.-Y., & Vilca-Cutipa, G. (2026). Factor structure of artificial intelligence use in university teaching pedagogy. *Contemporary Educational Technology*, 18(4), Article ep682. <https://doi.org/10.30935/cedtech/19132>
- Fusch, P., Fusch, G., Ness, L. (2018). Denzin's paradigm shift: Revisiting triangulation in qualitative research. *Journal of Social Change*, 10(1), 19-32. <https://doi.org/10.5590/JOSC.2018.10.1.02>
- Gerlich, M. (2024). Navigating trust and anxiety: Understanding public perceptions of IA and their implications for ethical IA integration. In *Proceedings of the International Experts Summit on Artificial Intelligence and Machine Learning*. <https://doi.org/10.2139/ssrn.4972893>
- Hu, L., & Bentler, P. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, 6(1), 1-55. <https://doi.org/10.1080/10705519909540118>
- International Business Machines. (2026a). IBM SPSS Amos. *IBM*. <https://www.ibm.com/products/structural-equation-modeling-sem>
- International Business Machines. (2026b). IBM SPSS statistics. *IBM*. <https://www.ibm.com/products/spss-statistics>

- Iraola-Real, I., Vasquez, C., Diaz-Leon, I., & Iraola-Arroyo, A. (2023). Self-efficacy and digital anxiety and their influence on virtual educational performance: A diagnostic study in a sample of students from a private university in Lima – Peru. *International Journal of Emerging Technologies in Learning*, 18(9), 165-179. <https://doi.org/10.3991/ijet.v18i09.36183>
- Isma'il, A., & Ibrahim, H. B. (2025). Teachers' professional identity in the era of artificial intelligence: A phenomenological study. *International Journal of Professional Development, Learners and Learning*, 7(2), Article e2517. <https://doi.org/10.30935/ijpdll/17416>
- Keravnos, N., & Eleftheriou, M. (2026). Trust as a mediating mechanism in ai-enabled school leadership: Navigating benefits, risks, and ethical tensions in Education 4.0. *Educational Point*, 3(3), Article e182. <https://doi.org/10.71176/edup/18914>
- Khor, T., Chan, L., Koh, E., & Seow, P. (2026). Exploring students' perceptions of generative AI-generated feedback in learning programming. *Educational Psychology*, 46(1), 150-182. <https://doi.org/10.1080/01443410.2025.2564894>
- Klimova, B., & Pikhart, M. (2025). Exploring the effects of artificial intelligence on student and academic well-being in higher education: A mini-review. *Frontiers in Psychology*, 16. <https://doi.org/10.3389/fpsyg.2025.1498132>
- Kuleto, V., Ilić, M., Dumangiu, M., Ranković, M., Martins, O., Păun, D., & Mihoreanu, L. (2021). Exploring opportunities and challenges of artificial intelligence and machine learning in higher education institutions. *Sustainability*, 13(18), Article 10424. <https://doi.org/10.3390/su131810424>
- Liang, J., Stephens, J., & Brown, G. (2025). A systematic review of the early impact of artificial intelligence on higher education curriculum, instruction and assessment. *Frontiers in Education*, 10. <https://doi.org/10.3389/feduc.2025.1522841>
- Magaldi, D., & Berler, M. (2020). Semi-structured Interviews. In V. Zeigler-Hill, & T. K. Shackelford (Eds.), *Encyclopedia of personality and individual differences* (pp. 4825-4830). Springer. https://doi.org/10.1007/978-3-319-24612-3_857
- Mahmoud, A. (2025). The relationship of digital self-efficacy and future orientation with graduate students' attitudes towards the use of artificial intelligence applications in scientific research. *Al-Azhar Journal of Education*, 44(205), 305-398. <https://doi.org/10.21608/JSREP.2025.422550>
- Moon-Yong, K., & Heayon, Ch. (2025). Prior AI experience and attitude toward AI-based smart home services: A moderated mediation model of perceived benefits of AI and digital self-efficacy. *International Journal of Advanced Smart Convergence*, 14(1), 111-122. <https://doi.org/10.7236/IJASC.2025.14.1.111>
- Morandín-Ahuerma, F. (2023). *Principios normativos para una ética de la inteligencia artificial* [Normative principles for an ethics of artificial intelligence]. OSF. <https://doi.org/10.31219/osf.io/dgnq8>
- Mortensen, O. (2024). How many users does ChatGPT have? Statistics & facts (2025). *SEO.AI*. <https://seo.ai/blog/how-many-users-does-chatgpt-have>
- Nazaretsky, T., Cukurova, M., & Alexandron, G. (2022). An instrument for measuring teachers' trust in ai-based educational technology. In *Proceedings of the 12th International Learning Analytics and Knowledge Conference* (pp. 56-66). ACM. <https://doi.org/10.1145/3506860.3506866>
- Peker, C. (2026). Optimal linear aggregation of correlated expert judgments. *Economics Letters*, 261, Article 112855. <https://doi.org/10.1016/j.econlet.2026.112855>
- Qing, G., Muhd, O., & Ahmad, H. (2026). Teachers' professional development on self-efficacy, attitudes, and digital competencies in the digital era. *Acta Psychologica*, 265, Article 106683. <https://doi.org/10.1016/j.actpsy.2026.106683>
- Saborío-Taylor, S., & Rojas-Ramírez, F. (2024). Universal design for learning and artificial intelligence in the digital era: Fostering inclusion and autonomous learning. *International Journal of Professional Development, Learners and Learning*, 6(2), Article ep2408. <https://doi.org/10.30935/ijpdll/14694>
- Salas-Pilco, Z., & Yang, Y. (2022). Artificial intelligence applications in Latin American higher education: A systematic review. *International Journal of Educational Technology in Higher Education*, 19, Article 21. <https://doi.org/10.1186/s41239-022-00326-w>
- Samuel, S., & Merkebu, J. (2026). Exploring sampling strategies to maximize qualitative research studies in adult education. *Adult Learning*, 37(2), 89-99. <https://doi.org/10.1177/10451595251349183>

- Silva, G., Oliveira, G., & Silva, M. (2021). Estudo de caso único: Uma estratégia de pesquisa [Single case study: A research strategy]. *Revista Prisma*, 2(1), 78-90. <https://revistaprisma.emnuvens.com.br/prisma/article/view/44>
- Storozhyk, M. (2024). Philosophy of future: Analytical overview of interaction between education, science, and artificial intelligence in the context of contemporary challenges. *Futurity Philosophy*, 3(1), 23-47. <https://doi.org/10.57125/FP.2024.03.30.02>
- Taber, S. (2018). The use of Cronbach's alpha when developing and reporting research instruments in science education. *Research in Science Education*, 48, 1273-1296. <https://doi.org/10.1007/s11165-016-9602-2>
- Turing, A. (1950). Computing machinery and intelligence. *Mind*, LIX, 433-460. <https://doi.org/10.1093/mind/LIX.236.433>
- United Nations Educational, Scientific and Cultural Organization. (2024). Guía para el uso de IA generativa en educación e investigación [Guide to the use of generative AI in education and research]. UNESCO. <https://unesdoc.unesco.org/ark:/48223/pf0000389227.locale=es>
- University of Oxford. (2021). Informed consent. *University of Oxford*. <https://researchsupport.admin.ox.ac.uk/governance/ethics/resources/consent#collapse281091>
- Usak, M. (2024). Artificial intelligence in biology education. *Journal of Baltic Science Education*, 23(5), 806-808. <https://doi.org/10.33225/jbse/24.23.806>
- Uygun, E. (2026). Clashing AIs: Artificial intelligence literacy and academic integrity in an EFL context. *Journal of Academic Ethics*, 24, Article 7. <https://doi.org/10.1007/s10805-025-09676-2>
- Venkatesh, V., Morris, G., Davis, G., & Davis, D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425-478. <https://doi.org/10.2307/30036540>
- Wang, Sh., Sun, Z., Wang, H., Yang, D., & Zhang, H. (2025). Enhancing student acceptance of artificial intelligence-driven hybrid learning in business education: Interaction between self-efficacy, playfulness, emotional engagement, and university support. *The International Journal of Management Education*, 23(2), Article 101184. <https://doi.org/10.1016/j.ijme.2025.101184>
- Zada, A., & Urquhart, C. (2026). 5: Open coding qualitative data: An essential first step in grounded theory analysis. In G. Hadley, & A. Bryant (Eds.), *Grounded theory in action* (pp. 60-68). Edgar Online. <https://doi.org/10.4337/9781035321919.00012>
- Zhou, C., & Wang, Y. (2026). University students' writing feedback literacy in the AI era: The interplay of generative AI acceptance, writing anxiety and writing self-efficacy in Chinese EMI educational contexts. *European Journal of Education*, 61(1) Article e70478. <https://doi.org/10.1111/ejed.70478>

APPENDIX A

Table A1. Reliability analysis by item (in Latin Spanish)

Dimensions	Items	CT	CA
Perception of the benefits of AI	1. Las herramientas basadas en IA me ayudan en la realización de tareas como la resolución de problemas, la redacción de textos, la elaboración de esquemas o mapas conceptuales, entre otras	.53	.90
	2. La IA me ayuda en el autoaprendizaje de los diversos cursos.	.51	.89
	3. La IA me ayuda a crear agentes inteligentes (robots o software) que pueden servir como compañeros de aprendizaje	.46	.90
	4. La IA puede ayudar a los profesores a asignar tareas personalizadas que se ajusten a las necesidades de los estudiantes.	.63	.89
	5. La IA puede ayudar a los profesores con las actividades de gestión durante la clase.	.61	.89
	6. La IA puede ayudar a los profesores a planificar sus actividades educativas antes de la hora de clase.	.54	.90
	7. La IA puede mejorar la labor de los docentes, por ejemplo, utilizando avatares basados en IA para simular escenarios de enseñanza.	.55	.90
Reasons for not trusting AI	8. Considero que si existen discrepancias entre la evaluación generada por la IA y la evaluación del profesor.	.41	.90
	9. Considero que los desarrolladores de IA carecen de experiencia sobre la realidad educativa universitaria.	.38	.90
	10. Considero que los algoritmos de IA no entienden los factores sociales, emocionales y motivacionales que son muy importantes en el aprendizaje.	.36	.90
	11. Considero que la intuición de los profesores es superior a la de la IA.	.33	.90
	12. Considero que los algoritmos de IA no conocen el historial de aprendizaje del estudiante fuera de la universidad.	.37	.90
	13. Considero que existe falta de transparencia en la forma en que la IA toma decisiones para evaluar el aprendizaje de los estudiantes.	.42	.90
	14. Considero que la IA elimina la autonomía de los profesores.	.31	.90
	15. Considero que cuando la IA se vuelva más frecuente, se necesitarán menos docentes.	.25	.90
Working with AI for improved pedagogy	16. Considero que el uso de los datos por la IA plantea riesgos para la privacidad de los alumnos.	.29	.90
	17. Confío plenamente en el uso de herramientas personalizadas basadas en IA para el desarrollo de mis tareas.	.48	.89
	18. Creo que tendré éxito en el uso de herramientas basadas en IA para personalizar mi aprendizaje cuando estén disponibles para mí.	.71	.89
	19. Considero que usaré herramientas personalizadas basadas en IA para mejorar mi rendimiento en las diferentes clases.	.65	.89
	20. Considero que el uso de herramientas basadas en IA implicará un cambio significativo en la forma en que aprendo.	.67	.89
	21. Considero que a medida que las herramientas basadas en IA para el aprendizaje personalizado se vuelvan más frecuentes, ganaré confianza en su uso.	.65	.89
	22. Cuanto más comprenda cómo una herramienta de IA toma decisiones, más confianza tendré en ella.	.62	.89
	23. Cuantos más datos estén disponibles para las herramientas basadas en IA, más confianza puedo tener en la precisión de sus conocimientos.	.61	.89
	24. Confío en la recomendación de una herramienta basada en IA al menos tanto como en la recomendación de un profesor o compañero de aula.	.51	.90
	25. Confío en la recomendación de una herramienta basada en IA al menos tanto como en la recomendación de un experto, como de un investigador calificado en su especialidad.	.50	.90

Note. CT: Corrected total element correlation & CA: Cronbach's alpha if the item is deleted

