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Regular Article

AI in academia: How do social influence, self-efficacy, and integrity influence researchers' use of AI models?

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ABSTRACT

The integration of artificial intelligence models into academic settings has experienced remarkable growth in recent years. Given that researchers' interactions with and perceptions of these technologies can substantially influence academic procedures and outputs, identifying the key determinants of their incorporation into university environments is crucial. This investigation pursued two main objectives: first, to identify the variables that condition the implementation of AI models in research activities, and second, to analyze how perceived ethical considerations and academic integrity influence their adoption. The empirical study was conducted through a digital survey administered to 302 academic researchers from Peruvian public and private universities. The analytical methodology employed structural equation modeling and confirmatory factor analysis, grounded in an expanded version of the Unified Theory of Acceptance and Use of Technology 2 model. The results demonstrated that six out of nine hypotheses were supported; social influence, educational self-efficacy, and academic integrity were identified as primary factors predicting researchers' use of AI models. Effort expectancy had a significant negative effect on AI model use. Furthermore, the use of AI models was found to significantly influence both teachers' concerns and perceived ethics among academics. Notably, performance expectancy, technological self-efficacy, and personal anxiety did not significantly affect AI model use. This study contributes to the understanding of AI adoption in academic research by highlighting the importance of social, educational, and ethical factors. These findings have implications for developing policies and training programs to promote responsible AI use in higher education and suggest a need to reevaluate traditional technology acceptance models in the context of AI in academia.

1. Introduction

The incorporation of artificial intelligence (AI) within the realm of higher education has engendered a multitude of substantial opportunities alongside notable challenges. The integration of AI holds significant promise for the improvement of educational quality, the refinement of teaching methodologies, and the advancement of assessment techniques, all while equipping students for their prospective careers (Ali & Abdel-Haq, 2020; Bond et al., 2024; Carrión Montalván, Pillajo Angos, Castellanos Fonseca, & Vega Aguaiza, 2024; Kuka, Hörmann, & Sabitzer, 2022; Marengo, Pagano, Pange, & Soomro, 2024; Rong, Xiao, Kong, & Gao, 2023; Slimi & Carballido, 2023; Zawacki-Richter, Marín, Bond, & Gouverneur, 2019). However, its implementation faces obstacles such as technical infrastructure, data privacy, and ethical concerns (Marengo et al., 2024; Rong et al., 2023).

The diversity and complexity of AI technologies in academic settings warrant careful consideration. Different AI programs serve distinct purposes with varying implications, from generative models that produce academic writing to detection tools that authenticate human authorship and from research assistants that analyze data to systems that

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automate administrative tasks. The efficacy of these tools varies significantly, as measured by key performance metrics such as accuracy, precision, recall (sensitivity), and F1 scores. These variations in performance capabilities directly influence their potential impact on academic work and raise distinct ethical considerations. For example, while highly accurate plagiarism detection AI may enhance academic integrity, imperfect generative models might compromise research quality. Furthermore, research suggests that academics' attitudes toward AI adoption are significantly influenced by specific tool characteristics, including their intended use, performance quality, and target users (Bhardwaj et al., 2024, pp. 204–215; Chen et al., 2024). This heterogeneity in AI capabilities and applications necessitates a nuanced understanding of how different AI tools are perceived and adopted within academic research contexts rather than treating AI as a monolithic technology.

The use of AI models by university professors has sparked a debate on ethical implications and academic integrity (Carrión Montalván et al., 2024; Slimi & Carballido, 2023). Risks such as algorithmic bias, data leakage, and reduced autonomy have been identified (Bond et al., 2024), along with an increase in plagiarism and academic fraud (Pierres, Christen, Schmitt-Koopmann, & Darvishy, 2024).

With respect to academic activity, AI has created both opportunities and challenges for higher education institutions. In particular, the use of AI models by university professors has raised significant ethical and academic integrity concerns in teaching and research (Fernández-Miranda, Román-Acosta, Jurado-Rosas, Limón-Dominguez, & Torres-Fernández, 2024; Meza et al., 2024). This study aims to examine the factors influencing faculty decisions to use these tools, focusing specifically on the role of ethical perceptions and principles of academic integrity (Acosta-Enriquez et al., 2024a).

The integration of AI into universities has raised numerous ethical questions among academics, from a lack of algorithmic transparency to the identification of ethical biases (Fernández-Miranda et al., 2024). This is especially true in the Latin American context, where emerging ethical challenges related to AI implementation in universities have been identified (Fernández-Miranda et al., 2024). In contrast, a study conducted in Bangladesh demonstrated a positive correlation with the growing trend of AI utilization in higher education, highlighting variability in the adoption and perception of these technologies across different geographical and cultural contexts (Ahmed, 2024).

The widespread use of generative AI tools in learning contexts has intensified concerns about academic integrity, leading some institutions to prohibit their use in academic work, whereas others explore their potential benefits (Meza et al., 2024; Milinković, Vuleta, & Babić, 2024). This dichotomy reflects the complexity of the debate surrounding AI in higher education, where the goal is to balance innovation with the preservation of traditional academic values (Solórzano Solórzano et al., 2024).

Recent studies have identified ethical implications such as algorithmic bias, private data leakage, and reduced autonomy in the use of AI models in the classroom (Ahmed, 2024). Moreover, fundamental ethical principles such as fairness, privacy, transparency, and responsibility have been established (Ahmed, 2024). In this context, researchers play crucial roles in ensuring data integrity, maintaining research reproducibility, and promoting responsible AI use in academic activities (Milinković et al., 2024).

Students' perceptions of AI tools also play a crucial role in this debate. A study revealed a trend among undergraduate students favoring commercial AI tools not specifically designed for educational use, suggesting a possible deficiency in the domain of educational AI (da Silva et al., 2024; Acosta-Enriquez et al. (2024 b). This preference raises questions about the adequacy of available tools and the need to develop solutions tailored to the academic context.

The extensive adoption of AI tools among university students has resulted in an increase in plagiarism and academic fraud, highlighting the need for effective technology implementation and the formulation of clear objectives and policies for the equitable, inclusive, and ethical utilization of AI to address academic misconduct (Song, 2024). Additionally, an ethical framework is essential to maximize the benefits and mitigate the challenges associated with the integration of AI in education (Unesco, 2024). This situation has prompted a reevaluation of the intricate dynamics related to academic integrity and the processes of learning and assessment at the university level (Milinković et al., 2024; Navarro-Dolmestch, 2023).

Despite the growing interest in AI integration in higher education, there is a significant knowledge gap regarding the predictors of AI model use in scientific research by university professors. First, a low level of AI knowledge among university professors has been identified- (Altememy et al., 2023). A study conducted in Peru revealed that 41.8% of faculty members had limited knowledge of AI, suggesting a significant gap in understanding and applying these technologies in the educational field (Estrada-Araoz et al., 2024). This lack of knowledge raises questions about the factors that could predict the adoption and effective use of AI models in academic research. Additionally, while AI integration in university research has revolutionized traditional research methods (Meza et al., 2024), there is little information on the specific factors that predict its adoption by professors. The lack of transparency in algorithms and ethical biases, along with the ethical problems related to the use of AI in university research (Meza et al., 2024), highlight the need for a greater understanding of how academics' decisions to employ these tools are influenced by their ethical perceptions. On the other hand, while studies such as those conducted at the University of Guayaquil have demonstrated the significant impact of AI-based tools on academic performance (Pacheco-Mendoza, Guevara, Mayorga-Albán, & Fernández-Escobar, 2023), there is a lack of research exploring how this perceived impact might predict the use of AI by professors. Finally, although a bibliometric review has highlighted sustained interest in investigating the acceptance of AI technologies in higher education (Flores-Velásquez et al., 2024), few studies have specifically examined the predictors of use among university professors while considering factors such as perceived ethics and academic integrity.

This study aims to analyze the predictors of AI model use among researchers, including university professors, master's and doctoral students, and academic researchers. This study offers two important innovations: on the one hand, it analyzes the effects of UTAUT2 constructs such as performance expectancy, effort expectancy, social influence, technological self-efficacy, educational self-efficacy, and personal anxiety on AI model use; on the other hand, it examines the role of perceived ethics, academic integrity, and faculty concerns in the use of AI models in research (Acosta-Enriquez et al., 2024c). While previous research has extensively documented the transformative impact of AI in academia, ranging from improved learning analytics (Bond et al., 2024) to enhanced research methodologies (Meza et al., 2024), significant knowledge gaps remain in understanding the factors that influence AI adoption among academics. Specifically, while the UTAUT2 model has proven valuable in analyzing technology acceptance in educational contexts (Milinković et al., 2024), it does not adequately address the unique ethical dimensions of AI adoption in academic research. Traditional UTAUT2 constructs focus primarily on technological and social factors, overlooking the critical role of ethical considerations and academic integrity in researchers' decision-making processes. This study addresses this gap by integrating ethical perceptions and academic integrity concerns into the UTAUT2 framework, responding to the growing evidence that ethical considerations significantly influence AI adoption in academic settings (Farina & Stevenson, 2024; Fernández-Miranda et al., 2024). Furthermore, while existing research has identified specific challenges such as algorithmic bias and data privacy concerns (Marengo et al., 2024), little is known about how these ethical considerations interact with traditional technology acceptance factors in shaping AI adoption among university researchers.

From a theoretical perspective, this study contributes to the body of knowledge on technology adoption in higher education, specifically exploring how constructs of perceived ethics and academic integrity influence university professors' decisions. By examining these predictors, we seek to expand existing models of technology acceptance in the specific context of AI in higher education.

Socially, this research is relevant because it addresses the ethical and integrity concerns that arise with the introduction of AI in higher education. A better understanding of these aspects can help ensure that AI implementation in universities is carried out in a way that preserves the fundamental values of education and promotes equity and inclusion.

From a pragmatic perspective, the findings of this study can offer significant insights for the formulation of transparent institutional policies and thorough ethical guidelines. This is essential to guarantee that the incorporation of AI in higher education is in harmony with the fundamental principles of academic integrity and social responsibility (Farina & Stevenson, 2024). Moreover, it can assist educational institutions in formulating more impactful training and support initiatives for faculty regarding the ethical and responsible application of AI.

2. Literature review

2.1. Impact and use of AI in higher education

The integration of AI into higher education has significantly transformed educational and research processes. A bibliometric study revealed a substantial increase in research production related to AI, particularly in machine learning, data mining, and learning analytics (Ateeq, Alaghbari, Alzoraiki, Milhem, & Hasan Beshr, 2024). This growth reflects the importance that the academic community places on AI within the university context.

AI redefines the educational experience by offering personalized learning pathways and enhancing student engagement (W. Ali, Alami, Alsmairat, & Almasaeid, 2024; Al-Zahrani & Alasmari, 2024; Cildir, 2024; Ghandour, 2024). In the research domain, AI has revolutionized traditional methods, enabling the processing of large datasets and the generation of predictive insights (Al-Zahrani & Alasmari, 2024). This not only increases research productivity but also opens new avenues for discovery across various academic disciplines.

A crucial aspect is AI's impact on preparing students for their future careers. AI has the potential to enhance educational quality and provide practical teaching and learning methods that better align with labor market demands (Slimi & Carballido, 2023). This underscores the need for higher education institutions to adopt AI to remain relevant and competitive (Abdulmuhsin, Hussein, AL-Abrrow, Masa'deh, & Alkhwaldi, 2024; Al-Adwan et al., 2023; Alkhwaldi, 2023, 2024).

In line with these advancements, a positive impact has been observed in grounded learning experiences, administrative optimization, and data-driven decision-making (Samman, 2024). This highlights AI's transformative potential to reshape higher education at multiple levels.

However, the implementation of AI also presents significant challenges. There is growing concern about global inequality and the uneven distribution of AI resources, which could exacerbate existing educational disparities (Aktürk, 2024). Additionally, the rapid pace of technological evolution risks leaving educational discourse lagging in understanding the pros and cons of AI (Cildir, 2024; Ghandour, 2024).

To address these challenges, researchers emphasize the need to develop comprehensive ethical frameworks and precise guidelines for AI use in higher education (Cildir, 2024; Farina & Stevenson, 2024; Ghandour, 2024).). These frameworks must align with the core values of academic integrity and social responsibility.

Ongoing training for educators and stakeholders is crucial for ensuring a proper understanding of the ethical considerations and implications of AI in the educational sector (Helmiatin, Hidayat, & Kahar, 2024). In response to this need, a model has been proposed to accelerate AI adoption in higher education, highlighting the importance of continuous training (Helmiatin et al., 2024).

Moreover, it is essential to align AI applications with specific educational goals. Studies suggest that AI should complement, rather than replace, the human aspects of education (Al Daraai, Al Maqrashi, Al Zakwani, & Al Shaikh, 2024). This perspective aligns with the need to balance technological innovation with traditional educational values.

In conclusion, while AI offers significant opportunities to enhance higher education, it is imperative to adopt a balanced approach that considers both its capabilities and limitations. The successful implementation of AI requires a comprehensive understanding that encompasses not only technical aspects but also ethical, social, and educational dimensions (Al-Zahrani & Alasmari, 2024; Samman, 2024). This framework provides a solid foundation for exploring the predictors of AI model use among university faculty, considering the crucial role of perceived ethics and academic integrity in this evolving context.

2.2. Use of AI models in scientific research

In the realm of academic research, AI models such as ChatGPT, Claude, and ScopusAI have demonstrated their potential to increase the efficiency, clarity, and precision of scientific communication (Bhardwaj et al., 2024, pp. 204–215; Bin-Nashwan, Sadallah, & Bouteraa, 2023; Chen et al., 2024). These technologies not only facilitate the drafting of outlines and initial manuscripts but also assist in title composition and the overall structuring of academic papers [8]. Beyond writing, AI is being applied in various research methodologies, optimizing processes such as systematic literature reviews (Chen et al., 2024; Tamanna & Sinha, 2024).

However, the use of AI in scientific research presents significant challenges. Concerns about academic integrity and research ethics are paramount (Ateeq et al., 2024; Bhardwaj et al., 2024, pp. 204–215; Bin-Nashwan et al., 2023; Christou, 2023). Questions arise regarding the originality of work, proper attribution of authorship, and the risk of unintentional or AI-assisted plagiarism (Bin-Nashwan et al., 2023; Chen et al., 2024). These ethical challenges underscore the need for clear principles and guidelines for the ethical use of AI in academic work (Ateeq et al., 2024; Christou, 2023).

The impact of AI on research reproducibility is another crucial aspect. While AI can enhance the consistency and replicability of studies, it also raises challenges regarding transparency and understanding of the underlying processes (Bhardwaj et al., 2024, pp. 204–215). Researchers play a fundamental role in ensuring data integrity and mitigating potential biases in the use of AI (Bhardwaj et al., 2024, pp. 204–215).

The limitations of AI models in academic research include concerns about generating unreliable research, introducing algorithmic biases, and the potential loss of autonomy in the research process (Christou, 2023; Tang & Su, 2024). These challenges highlight the importance of maintaining a critical and reflective approach to the use of AI.

In the future, the impact of AI on academic research promises to be profound. AI-powered tools have the potential to transform not only research but also academic publishing and university libraries (Hörmann, Kuka, Fraser, & Sabitzer, 2024; Yaroshenko & Iaroshenko, 2023). However, this proliferation of AI models is also creating new power imbalances, raising significant ethical concerns for the academic community (Ghio, 2024).

While UTAUT2 has provided valuable insights into technology adoption in various contexts, its application to AI adoption in Latin American higher education, particularly in Peru, reveals significant contextual gaps. Recent studies in the Peruvian context have highlighted unique challenges, such as the finding that 41.8% of faculty members have limited AI knowledge (Estrada-Araoz et al., 2024), suggesting that standard UTAUT2 constructs may not fully capture the complexities of AI adoption in this setting. Furthermore, while traditional UTAUT2 research focuses on technological and social factors, the ethical dimensions of AI adoption in academic research require special consideration, particularly in emerging economies where ethical frameworks for AI use are still developing (Fernández-Miranda et al., 2024). The intersection of technology acceptance and ethical considerations in AI adoption presents a unique theoretical challenge that extends beyond conventional UTAUT2 applications. For example, studies at Peruvian universities have shown that ethical concerns about AI use are deeply intertwined with cultural and institutional factors (Meza et al., 2024), suggesting that ethical considerations may moderate or mediate the relationship between traditional UTAUT2 constructs and AI adoption. This complex interplay between ethical considerations and technology acceptance factors remains understudied, particularly in contexts where institutional policies and ethical guidelines for AI use are still evolving (Solórzano Solórzano et al., 2024).

2.3. Role of perceived ethics and academic integrity in the use of AI models in scientific research

The ethical perceptions of researchers play a crucial role in the adoption of AI models in scientific research. Academics are at the forefront of this effort and are responsible for ensuring data integrity, maintaining research reproducibility, and mitigating potential biases (Bhardwaj et al., 2024, pp. 204–215). However, the lack of ethical knowledge and the existence of unclear principles pose significant obstacles to adequately considering ethics in the use of AI (Khan et al., 2022). This, in turn, could negatively impact the adoption of robust ethical principles in the implementation of these technologies.

Academic integrity lies at the heart of this debate. On the one hand, AI tools hold the promise of enhancing plagiarism detection, preventing fraud, and fostering more responsible research practices (Madhu, Manoj Kumar, Pratyaksha, Sushmita, & Javed, 2023). In line with this idea, an academic integrity model (AIM) has been proposed, emphasizing the importance of developing sociotechnical responsibility in students and addressing issues such as contract cheating, collusion, and plagiarism (Bhardwaj et al., 2024, pp. 204–215). Ironically, however, the same technology that is supposed to protect academic integrity has also brought forth new kinds of wrongdoing, such as advanced plagiarism using AI algorithms and data fabrication (Chen et al., 2024).

Maintaining ethical standards in the development and use of AI models in scientific research presents complex challenges. These include issues of transparency and replicability of AI systems, concerns about data privacy, considerations of fairness and equity, and the fear of a potential "algocracy" that could undermine human autonomy in research (Gao, Haverly, Mittal, Wu, & Chen, 2024). In response to these concerns, there is an urgent need to address the ethical dilemmas posed by algorithmic biases, lack of transparency, and the potential social repercussions of AI applications in research (Kumar, Joshi, Sharan, Peng, & Dudhagara, 2024).

To address these challenges, it is crucial for the academic community to adopt a proactive approach. This involves strengthening ethical standards, enhancing researchers' training on the ethical aspects of AI, and establishing rigorous review mechanisms that ensure responsible and transparent research processes (Chen et al., 2024). In line with this need, some scholars have proposed ethical frameworks for peer review in specific fields, such as nephrology, which could serve as models for other disciplines (Morrison et al., 2023).

In conclusion, the role of perceived ethics and academic integrity in the use of AI models in scientific research is fundamental to maintaining public trust in science. The scientific community faces the challenge of developing and applying comprehensive guidelines that address integrity in AI-powered research (Chen et al., 2024). This theoretical framework underscores the need for a balanced approach that leverages the benefits of AI in scientific research while proactively addressing the ethical and integrity challenges that arise with its implementation. Only through continuous dialog and critical reflection can we ensure that AI becomes a tool that enriches, rather than compromises, the integrity and value of scientific research.

2.4. UTAUT2 and the constructs predicting the behavioral use of AI models in academia

The proposed research model is shown in Fig. 1 and is composed of ten constructs and nine hypotheses, which are supported below: At the core of the UTAUT2 are several key constructs that influence technology adoption. Among future mathematics teachers in China, performance expectancy, which refers to the belief that technology enhances performance, has proven to be a significant factor in the intention to use AI chatbots (Wijaya, Su, Cao, Weinhandl, & Houghton, 2024). Similarly, effort expectancy, which reflects perceived ease of use, has been shown to have an effect on usage behavior, although its influence on behavioral intention may vary depending on the context (Zhu et al., 2024).

Research on social influence, which represents perceived pressure from the environment to use technology, has yielded mixed results. For instance, in the hospitality industry, its impact on AI usage is minimal (Gajić et al., 2024). Facilitating conditions, referring to the available technical and organizational support, have demonstrated a limited but measurable impact on behavioral intention (Gajić et al., 2024).

Other important constructs of UTAUT2 include hedonic motivation, which positively influences university students' intention to use generative AI products (Zhu et al., 2024), and habits, which have been shown to significantly affect both behavioral intention and actual use in various studies, including the acceptance of ChatGPT in higher education (Strzelecki, 2023; Tian, Ge, Zhao, & Zheng, 2024).

Interestingly, the price value, another UTAUT2 construct, did not have a significant effect on behavioral intention in the context of university students using generative AI products (Zhu et al., 2024). This could suggest that, in the academic sphere, the perceived cost of technology may not be a determining factor in its adoption.

The UTAUT2 model has demonstrated its versatility by being applied and extended across various educational contexts. For example, it has been used to study the acceptance of AI chatbots by future teachers (Wijaya et al., 2024), the use of generative AI products by university students (Zhu et al., 2024), and the acceptance of ChatGPT in higher education (Strzelecki, 2023). Additionally, it has been applied in related contexts such as the hospitality industry (Gajić et al., 2024), the healthcare sector (Tian et al., 2024), and English as a Foreign Language (EFL) learning (Zheng, Wang, Liu, & Jiang, 2024).

However, the UTAUT2 model also has limitations. Some studies have shown that its performance in educational contexts may be lower than that reported in the initial UTAUT2 study (Or, 2023). Furthermore, it may have limitations in specific contexts, such as a lack of attention to particular issues and insufficient explanatory power in qualitative analyses (Zhao, Ni, Zhang, He, & Wang, 2024). Despite these limitations, UTAUT2 remains a valuable tool for understanding the adoption of AI models in academia. Its ability to incorporate ethical factors, such as ethical awareness and perceived risk (Strzelecki, 2023), makes it particularly relevant in the current context, where ethical considerations are increasingly important in the implementation of AI in educational settings.

2.5. Supporting the research hypothesis

PE has been identified as a crucial factor in the adoption and use of AI technologies in the academic field. Studies based on the unified theory of acceptance and use of technology (UTAUT) have demonstrated that PE significantly influences behavioral intention, which in turn affects the actual use of AI tools by university students (Altememy, Neamah, et al., 2023; Strzelecki & ElArabawy, 2024). Further research has revealed the substantial impact of AI technologies on students' academic performance, establishing a direct connection between AI capabilities in higher education institutions and the achievement of academic excellence (Altememy, Mohammed, et al., 2023).

PE has also been positively linked to student satisfaction and academic performance in the context of AI tool adoption (Dahri et al.,

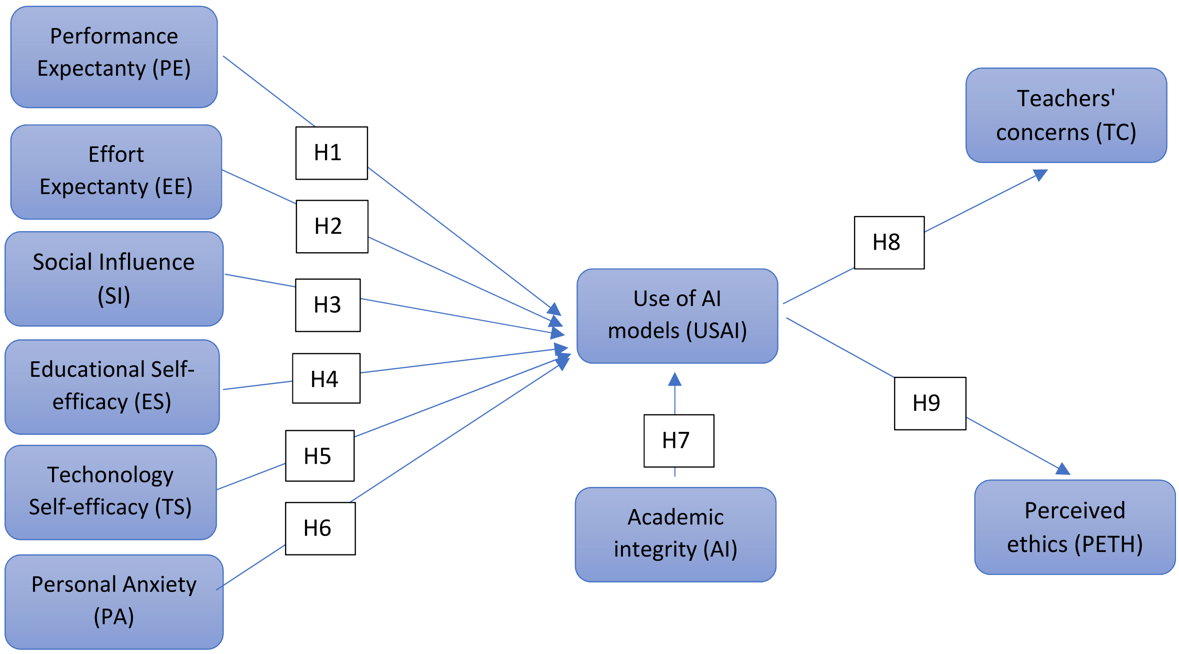

Fig. 1. Proposed model.

2024). However, it is important to consider the challenges associated with AI use, such as potential dependency and its effects on critical thinking (Zhang, Zhao, Zhou, & Kim, 2024), as well as the anxiety it may cause among educators (Funda & Piderit, 2024; Shahid, Zia, Bangfan, Iqbal, & Ahmad, 2024). On the basis of the reviewed literature, the following is proposed.

Hypothesis 1. Performance expectancy (PE) significantly influences the use of AI models (USAI) by university academics.

Effort expectancy (EE) has been identified as another crucial factor in the adoption and use of AI technologies in the academic field. Multiple studies based on UTAUT have shown that EE, along with performance expectancy, significantly influences the intention to use AI models by university academics (Alshare, El-Masri, & Lane, 2015; Andrews, Ward, & Yoon, 2021; Dahri et al., 2024; Duong, Bui, Pham, Vu, & Nguyen, 2023; Strzelecki & ElArabawy, 2024). Moreover, the integration of AI tools in higher education has shown a substantial positive effect on student engagement and academic performance (Ateeq et al., 2024; Funda & Piderit, 2024), suggesting that lower effort expectancy could encourage their adoption.

However, it is important to consider potential barriers to adopting AI models, such as anxiety and resistance to change among educators (Shahid et al., 2024), as well as the need to improve educators' preparedness to incorporate AI into their pedagogical approaches (Ateeq et al., 2024). The AI capabilities of higher education institutions and their impact on students' learning outcomes highlight the importance of addressing factors such as resources, skills, and awareness to enhance student self-efficacy (S. Wang, Sun, & Chen, 2023). On the basis of the reviewed literature, the following is proposed.

Hypothesis 2. Effort expectancy (EE) significantly influences the use of AI models (USAI) by university academics.

Social influence (SI) has been identified as a significant factor in the adoption and use of AI technologies in the academic field. Various studies based on UTAUT have demonstrated that SI, along with other factors such as performance expectancy and effort expectancy, significantly influences behavioral intention and the actual use of AI tools in higher education (Enriquez et al., 2024; Strzelecki & ElArabawy, 2024; Supianto et al., 2024).

Research has revealed that SI has a direct positive effect on the intention to use AI-enabled processes (Kandoth & Shekhar, 2022). Additionally, media attention to AI-related information and interpersonal communication about AI influence the perception of descriptive and injunctive norms regarding AI use (Li, Shi, Zhao, Zhang, & Zhong, 2024). Peer networks also play an important role in accelerating the diffusion of AI technology among academics (Soodan, Rana, Jain, & Sharma, 2024).

Perceived organizational support has also been shown to positively influence students' intention to use AI language models in learning courses (Hoi, Yu, & Ye, 2023), suggesting a similar effect on university academics. However, it is important to consider potential barriers and ethical considerations associated with integrating AI into higher education (Farina & Stevenson, 2024; Hassan, 2023; Sharma, Singh, Sharma, & Kapoor, 2024). On the basis of the reviewed literature, the following is proposed.

Hypothesis 3. Social influence (SI) significantly influences the use of AI models (USIs) by university academics.

The concept of educational self-efficacy (ES) has emerged as a pivotal element influencing the integration and application of AI technologies within academic settings. Research indicates that beliefs in one's academic self-efficacy play a crucial role in shaping both academic and career decisions, as do the motivational elements and learning strategies that foster successful academic outcomes (Greco et al., 2022).

Research has revealed that artificial self-efficacy positively influences teachers' perceived ease of use and attitudes toward adopting AI-based applications, ultimately affecting their intention to continue using AI in teaching (Sharma et al., 2024; Y. Wang, Liu, & Tu, 2021). Moreover, instructional self-efficacy has demonstrated the highest positive value in the relationship between management and AI utility, indicating the influence of untapped management potential (Elstad & Eriksen, 2024).

Importantly, integrating AI into higher education presents both opportunities and challenges. While AI technology has been shown to positively impact learning attitudes and behaviors (An & Ma, 2024), there are also concerns about problematic AI use, such as overreliance and a reduction in critical and independent thinking (Zhang et al., 2024).

In addition to being an important predictor of academic success (van Rooij, Jansen, & van de Grift, 2017), academic self-efficacy also predicts academic performance both directly and indirectly through the mediating role of academic engagement (Meng & Zhang, 2023). Consequently, the following theory is proposed.

Hypothesis 4. Educational self-efficacy (ES) significantly influences the use of AI models (USIs) by university academics.

Although the provided information does not directly address the relationship between technological self-efficacy (TS) and the use of AI models (USAI) by university academics, a connection can be inferred on the basis of related data. Technological self-efficacy, understood as an individual's confidence in their ability to use technology, appears to be a relevant factor in the adoption of advanced technologies such as AI in academic settings (Salhieh & Al-Abdallat, 2022).

Research suggests that academic self-efficacy has positive direct and indirect effects on entrepreneurial intention, which may extend to AI model adoption. Moreover, self-efficacy in information and communication technologies (ICTs) has a significant direct effect on the learning efficacy of AI-based technological applications among university students (Chou, Shen, Shen, & Shen, 2022). It is reasonable to assume that a similar effect could be observed among academics.

The progressive incorporation of AI has revolutionized university research (Meza et al., 2024), and its use in higher education institutions has the potential to improve academic outcomes and research capabilities (Farina & Stevenson, 2024). However, potential barriers to adoption exist, including ethical challenges (Meza et al., 2024; Tang & Su, 2024) and a negative correlation between age and overall learning self-efficacy (Al-Harthi, 2017).

Nonetheless, while more specific research is needed, these findings suggest that technological self-efficacy could play an important role in university academics' willingness to adopt and use AI models in their teaching and research practices. On the basis of the reviewed literature, the following is proposed.

Hypothesis 5. Technological self-efficacy (TS) significantly influences the use of AI models (USAI) by university academics.

Personal anxiety (PA) has been identified as a significant factor influencing the adoption and use of AI technologies in the academic field. Although most studies have focused on students, extrapolating these findings to university academics is reasonable.

Research based on the UTAUT has revealed that AI-related anxiety negatively affects the behavioral intention to use AI-based learning tools (Wen, Li, Zhou, An, & Zou, 2024). Specifically, AI learning anxiety and job replacement anxiety have been identified as factors that indirectly and negatively predict behavioral intention (Wen et al., 2024).

According to research on how AI affects college students' mental health, some AI systems provide individualized assistance that is good for students' learning and mental health, whereas others can make people anxious and stressed from having too much information and not enough face-to-face time with real people (Velastegui-Hernandez, Rodriguez-Pérez, & Salazar-Garcés, 2023). These findings suggest that personal anxiety could act as a potential barrier to AI adoption among university academics.

To mitigate the influence of personal anxiety on AI adoption, educators should cultivate AI literacy through comprehensive education and guide users in developing socially appropriate emotions through scientific psychological interventions (Wen et al., 2024). Additionally, the need to optimize AI and design tailored therapeutic interventions for the digital generation has been emphasized (Xie & Wang, 2024). Therefore, the following hypothesis is formulated.

Hypothesis 6. Personal anxiety (PA) significantly influences the use of AI models (USAI) by university academics.

Academic integrity (AI) has emerged as a crucial factor that significantly influences the adoption and use of AI models in the academic field. The growing integration of generative AI in education has raised concerns about academic integrity, particularly concerning assignments, projects, and assessments (Dhruv, Saha, Tyagi, & Jain, 2024).

Research indicates that the extensive adoption of AI tools among university students has led to an increase in plagiarism and cheating, highlighting the need for effective technology implementation and the development of clear objectives and policies for equitable, inclusive, and ethical AI utilization (Song, 2024). This suggests that university academics must carefully consider how to integrate AI models into their teaching and research practices without compromising academic integrity.

Teachers' perceptions of academic dishonesty in the context of AI indicate mixed views on the benefits of AI technologies for students, with concerns about their impact on academic integrity (Mohammadkarimi, 2023). This implies that academic integrity influences academics' decisions on how and when to use AI models in their academic activities.

To address these problems, it is imperative to formulate thorough ethical rules that guarantee that the integration and utilization of AI in higher education align with the fundamental principles of academic integrity and social responsibility (Farina & Stevenson, 2024; Perkins & Roe, 2023). This suggests that academic integrity influences not only the decision to use AI models but also how these technologies are implemented and regulated in academic settings. On the basis of the reviewed literature, the following is proposed.

Hypothesis 7. Academic integrity (AI) significantly influences the use of AI models (USAI) by university academics.

The use of AI models (USAI) has been shown to have a significant effect on teachers' concerns (TCs) in the academic field. Research reveals that university academics have varying degrees of familiarity with AI and, while they consider it a valuable educational tool, they also express concerns about its implementation (Abdelaal & Al Sawi, 2024).

Among the main concerns identified are difficulties in understanding AI algorithmic outputs, the financial implications of its implementation, data privacy, and the potential obsolescence of teachers (Abdelaal & Al Sawi, 2024). Moreover, ethical dilemmas related to the application of AI in academic research, including algorithmic opacity and the recognition of ethical biases, are significant concerns among faculty (Meza et al., 2024).

The integration of AI technology in educational environments has a substantial positive effect on student engagement and academic performance (Ateeq et al., 2024). However, this has also generated concerns about the potential displacement of human educators by AI systems and the potential dehumanization of pedagogy (Rosselló-Geli, 2023).

AI models transform how students approach report writing and research, requiring professors to adapt their assessment methods (Rosselló-Geli, 2023). This has led to the emergence of more robust assessment systems, resulting in higher levels of teacher engagement (Rahiman & Kodikal, 2024), but it has also generated questions about academic integrity and the authenticity of students' work. On the basis of the examined literature, the following is proposed.

Hypothesis 8. The use of AI models (USAI) significantly influences teachers' concerns (TCs) among university academics.

The use of AI models (USAI) has been shown to significantly influence the perception of ethics (PETH) among university academics. This influence manifests in various aspects of the academic environment and raises important ethical considerations.

The implementation of AI in academia raises complex ethical issues, including a lack of transparency in algorithms and the identification of ethical biases (Meza et al., 2024). These ethical challenges directly affect academics' perceptions of ethics in AI use.

While the utilization of AI in academia facilitates the practicality of research, it may also result in ethical dilemmas, including the devaluation of human authorship and unjust authorship (Dolunay & Temel, 2024). These concerns are associated with the emotional states and professional advancement objectives of academicians, which in turn affect their ethical assessments of AI.

The ethical considerations surrounding the deployment of AI models in educational settings encompass algorithmic biases and discrimination, potential breaches of data privacy, insufficient transparency, diminished autonomy, and the risk of academic misconduct (Tang & Su, 2024). These ethical concerns directly shape academics' perceptions of ethics in AI use.

The need for ethics courses in AI education at the university level (Raina, Mundra, Prasad, & Mishra, 2023) and considerations of AI's impact on human behavior and emotions (Ghotbi, Ho, & Mantello, 2022), as well as ethical awareness, perceived ethical risks, and ethical anxiety related to AI, play a significant role in behavioral intention and the use of generative AI products (Zhu et al., 2024), demonstrating how AI use influences academics' ethical perceptions. On the basis of the reviewed literature, the following is proposed.

Hypothesis 9. The use of AI models (USAI) significantly influences perceived ethics (PETH) among university academics.

3. Method

To evaluate the research hypotheses, the researchers undertook an empirical assessment grounded in the findings of Singh, Sinha, and Liébana-Cabanillas (2020). A survey was conducted among academic researchers who possess experience in utilizing various AI models, including large language models such as ChatGPT (versions 3.5 and 4.0), Claude, Gemini, and other AI research tools such as ScopusAI, Elicit, and ResearchRabbit. The survey aimed to collect insights regarding their perceptions and attitudes toward these technologies, with a particular focus on how these advanced AI models are integrated into their research workflows. This inclusive approach to different AI models was chosen to capture the diverse ways in which researchers interact with AI technologies in academic settings, recognizing that different models may serve distinct research purposes and potentially raise varying ethical considerations.

3.1. Participants

The study involved 302 academic researchers from public and private universities in Peru. A priori power analysis via G*Power 3.1 software indicated that a minimum sample size of 278 participants would be required to detect medium effect sizes ($f^2 = 0.15$) with 95% power at a significance level of $\alpha = 0.05$ for the structural equation model with 9 predictors. Therefore, our sample size of 302 participants exceeded the minimum requirement, ensuring adequate statistical power to detect significant effects. The sample was selected via nonprobabilistic accidental sampling, as described by Arrogante (2022). This method allowed for the inclusion of participants who were available and willing to voluntarily contribute to the research. While the nonprobabilistic sampling approach and geographical focus on Peruvian academics present certain limitations for generalizability, this methodological choice aligns with similar studies in technology adoption research. For example, comparable UTAUT2-based studies in higher education, such as research on AI adoption in Bangladesh (Ahmed, 2024) and Indonesia (Helmiatin et al., 2024), have successfully employed nonprobabilistic sampling. The focus on Peruvian universities provides unique insights into AI adoption in the context of an emerging economy, where technological infrastructure, institutional policies, and ethical frameworks may differ significantly from those in more studied regions. The sample's composition, with its high proportion of postgraduate students (59.3%) and early-career researchers, reflects the current demographic transformation in Peruvian academia, although it may not fully represent senior academics' perspectives. Additionally, the predominance of public university participants (62.33%) mirrors the national distribution of higher education institutions in Peru, enhancing internal validity while potentially limiting direct comparability with private sector-dominated systems. These sampling characteristics should be considered when interpreting the results, particularly when attempting to extrapolate findings to different cultural, economic, or institutional contexts. Future research could benefit from comparative studies across different Latin American countries or between emerging and developed economies to establish the broader applicability of these findings (Acosta-Enriquez et al., 2024a).

The majority of the respondents were from public universities (62.33%, 187 participants), whereas 37.7% (115 participants) were from private institutions (See Table 1). Regarding the sampling framework, from a total population of approximately 84,500 university academics in Peru (SUNEDU, 2023), we distributed the survey to 1250 researchers through institutional email lists and academic networks, resulting in 302 complete responses (24.16% response rate). The distribution proceeded through various channels: 45% through institutional email lists of public universities, 35% through private university networks, and 20% through academic research groups and professional associations. This distribution closely mirrors the national proportion of public versus private universities in Peru, where approximately 60% of universities are public institutions (SUNEDU, 2023). However, it is important to acknowledge the potential sampling bias inherent in the nonprobabilistic accidental sampling method used. While this response rate is comparable to that of similar studies in technology adoption research (Strzelecki & ElArabawy, 2024), it is important to note potential self-selection bias, as respondents might have been more predisposed to AI use. While the public−private distribution appears representative, the sample may overrepresent certain academic demographics, such as early-career researchers and postgraduate students, who comprised 59.3% of the respondents. Additionally, the concentration of participants in the 29–33 years age range (38.07%) suggests the possible underrepresentation of senior academics. These demographic characteristics should be considered when interpreting the findings, as they may not fully capture the perspectives of more experienced researchers or those in leadership positions. Furthermore, the sample's gender distribution (58.3% male, 41.7% female) generally aligns with the gender composition in Peruvian academia, although with a slightly greater representation of male participants than the national average.

In terms of educational level, postgraduate students predominated, accounting for 59.3% (178 participants) of the sample. They were followed by independent researchers, who accounted for 33.3% (100 participants) of the sample. With respect to the duration of ChatGPT usage, most participants (35.2%, 106 participants) reported having used it for 1–2 months, followed by those with 3–5 months of usage

Table 1
Sociodemographic attributes of the sample (n = 302).

Item		N	%
Gender	Male	176	58.3
	Female	126	41.7
Age	24-28	96	31.8
	29-33	115	38.07
	34-38	83	27.48
	39 to more	8	2.64
	Public	187	62.33
Type of university	Private	115	37.7
	Graduate student	178	59.3
Level of studies	Teacher/senior researcher	17	5.7
	Postdoctoral researcher	4	1.3
	Research Administrator	1	0.3
	Independent researcher	100	33.3
ChatGPT usage time	1–2 Months	106	35.2
	3–5 Months	75	24.9
	5–12 Months	54	17.9
	1–2 years	40	13.3
	More than 3 years	26	8.6

experience (24.9%, 75 participants).

3.2. Instruments

A data collection instrument was designed on the basis of the literature and the constructs of the UTAUT2 model, which also incorporates concepts of perceived ethics and academic integrity. The questionnaire was developed via the Google Forms platform and was structured in three main sections:

The first section contained informed consent, providing detailed information about the study and ensuring participants' anonymity. A branching question was included to confirm voluntary participation. The second section collected sociodemographic data, including age, sex, type of university, level of education and time of ChatGPT use.

The third section comprises the assessment items designed to measure the constructs of the proposed model. The instrument consists of 33 items distributed across ten constructs (Table 2): PE (3 items measuring perceived benefits and improvements in research performance), EE (4 items assessing ease of use and understanding), SI (3 items evaluating peer and institutional influence), ES (4 items measuring confidence in research abilities with AI), TS (4 items assessing general technological competence), PA (3 items measuring concerns and hesitations), AI (4 items evaluating ethical conduct and transparency), USAI (2 items measuring frequency and extent of use), PETH (4 items assessing ethical awareness and responsibility), and TC (2 items measuring faculty-specific concerns). All the items were adapted from validated scales in previous UTAUT2 studies and underwent expert review for content validity. All the items were measured via a 5-point Likert scale, where 1 represented 'strongly disagree' and 5 ′strongly agree'.

3.3. Data analysis details

The study was carried out between October 2023 and March 2024, a span of six months. Prior to data collection, the survey instrument underwent rigorous development and validation processes. First, we conducted a comprehensive literature review to develop operational definitions of AI models, which we defined to participants as "advanced computational systems capable of performing tasks that typically require human intelligence, specifically including large language models such as ChatGPT, Claude, and Gemini, as well as specialized research tools such as ScopusAI and ResearchRabbit." The initial survey items were developed through expert consultations and adapted from validated scales in previous UTAUT2 studies. Facial validity was established through review by a panel of five experts in educational technology and research methodology. A pilot test was conducted with 30 academics to assess item clarity and reliability, resulting in minor modifications to the wording of the questions and the elimination of ambiguous items. The final survey demonstrated good internal consistency, with Cronbach's alpha values ranging from 0.78 to 0.92 across the constructs. The researchers obtained permission from the selected public and private universities to conduct the empirical application of the survey. The form was disseminated via email and shared in WhatsApp groups of lecturers, with an accompanying glossary of AI-related terms to ensure consistent understanding among participants. The following approaches were employed for the analysis of the gathered data: Data cleaning was initially conducted via Microsoft Excel, eliminating missing values and incomplete surveys to maintain information quality. Subsequently, descriptive statistical techniques were applied to elaborate the sociodemographic results table, providing an overview of the characteristics of the sample. To evaluate the primary indicators of the validity and reliability of the measurement model, a confirmatory factor analysis (CFA) based on the maximum likelihood technique was conducted via the Lavaan package in the JASP program (JASP Team, 2024). Indicators such as average variance extracted (AVE) and factor loadings were employed in this procedure. In addition, to assess internal consistency reliability, the researchers used McDonald's omega

Table 2
Convergent validity tests.

Latent variable	AVE	Typical Error	Z value	Loadings	Items
Performance Expectancy (PE)	0.595	0.050	13.896	0.690	PE 1 Using AI models improves my performance in academic research.
		0.044	15.236	0.677	PE 2 Employing AI models enables me to achieve my research objectives more quickly.
		0.046	15.504	0.715	PE 3 Incorporating AI models increases my productivity as a researcher.
Effort Expectanty (EE)	0.650	0.045	15.033	0.677	EE1 Learning to use AI models for research is easy for me.
		0.040	16.253	0.653	EE 2 Interacting with AI models for academic research is clear and understandable.
		0.042	16.621	0.699	EE 3 I find it easy to be proficient in using AI models for research.
		0.039	17.384	0.682	EE 4 I find AI models easy to use in my research work.
Social Influence (SI)	0.604	0.048	11.296	0.544	YES 1 My research colleagues think I should use AI models.
		0.045	17.011	0.758	YES 2 The authorities at my institution are helpful in the use of AI models for research.
		0.048	16.009	0.767	YES 3 In general, my academic community supports the use of AI models in research.
Educational Self-efficacy (ES)	0.605	0.041	15.108	0.625	ES 1 I can design effective research studies incorporating AI models.
		0.039	16.292	0.635	ES 2 I feel able to adapt my research methods to the use of AI models.
		0.043	16.655	0.714	EN 3 I am confident in my ability to use AI models to improve the quality of my research.
		0.045	13.828	0.619	ES 4 Even without guidance, I can use AI models well in my research work.
Techonology Self-efficacy (TS)	0.556	0.043	15.689	0.672	TS1 I can complete a research task using AI models if someone shows me how to do it first.
		0.041	15.600	0.636	TS 2 I can complete a research task using AI models if I have reference manuals.
		0.048	12.485	0.605	TS 3 I can complete a research task using

(*continued on next page*)

Table 2 (*continued*)

Latent variable	AVE	Typical Error	Z value	Loadings	Items
					AI models if I see someone else using them before I try it myself.
		0.043	14.234	0.610	TS 4 I can complete a research task using AI models if I can call someone to help me if I get stuck.
Personal Anxiety (PA)	0.552	0.055	11.036	0.609	PA1 I worry that I might waste a lot of time exploring generative AI models for my research.
		0.059	11.851	0.694	PA 2 I hesitate to use AI models for research for fear of making mistakes that I cannot correct.
		0.061	10.634	0.651	PA 3 AI models intimidate me a bit when I use them for my research.
Academic integrity (AI)	0.545	0.048	11.638	0.558	AI 1 When using AI models in my research, I am always transparent about their use in publications and presentations.
		0.057	7.099	0.404	AI 2 I consider it against academic ethics not to disclose the use of AI models in the preparation of research manuscripts.
		0.044	14.889	0.661	AI 3 As a researcher, I am a role model in the ethical use of AI, citing and acknowledging its use when appropriate.
		0.043	16.166	0.694	AI 4 I am committed to using AI models with respect for intellectual property and copyright in my research.
Use of AI models (USAI)	0.713	0.049	15.633	0.773	USAI 1 I use AI models frequently in my research.
		0.049	15.950	0.780	USAI 2 I use AI models as long as I have access to them for my research projects.
Perceived ethics (PETH)	0.540	0.045	12.890	0.586	PETH 1 I believe it is ethical to use AI models to improve the efficiency and quality of my academic research.
		0.040	15.248	0.611	PETH 2 I consider that I have a responsibility to use AI models in a fair and nondiscriminatory manner in my research practice.
		0.045	13.488	0.607	PETH 3 I am alert to potential biases in the AI models I use in my research and take steps to mitigate them.
		0.045	14.674	0.662	PETH 4 I believe that the ethical use of AI models in research involves being transparent about their limitations and possible errors.
Teachers' concerns (TC)	0.541	0.055	11.930	0.653	PETH 4 I believe that the ethical use of AI models in research involves being transparent about their limitations and possible errors.
		0.052	13.600	0.701	TC2 I am concerned that I do not have the skills to effectively use AI models in my research.
		0.056	13.363	0.751	TC3 I am concerned that the use of AI models in research may perpetuate gender, racial, or cultural biases.

coefficient (ω), Jöreskog's ρ test and Dijkstra−Henseler's ρ test, abandoning the use of Cronbach's alpha coefficient in favor of more robust measures. Discriminant validity was evaluated via the Fornell and Larcker (1981) criterion and the heterotrait–monotrait ratio (HTMT) criterion, confirming sufficient differentiation between the model's constructs.

Finally, the research hypotheses were tested via partial least squares structural equation modeling (PLS-SEM). JASP statistical software was used to conduct this analysis (JASP Team, 2024).

4. Results

4.1. Results of the measurement model

Table 2 presents the results of the confirmatory factor analysis (CFA), where the factor loadings of the items are displayed. According to Hair (2009), factor loadings greater than 0.70 are considered acceptable, which is met in this study. Importantly, during the CFA process, the items USAI3 and TC1 were removed because the factor loadings were significantly below this threshold. Furthermore, all measured constructs exhibit values for the average variance extracted (AVE) that exceed the 0.50 threshold proposed by Hair, Sarstedt, Ringle, and Gudergan (2017). Finally, the item paths (Z values) range from 0.404 to 0.780, indicating that the paths are statistically significant.

Table 3 presents the findings of the reliability and discriminant validity assessments. To assess the reliability of the constructs, Jöreskog's ρ, Dijkstra–Henseler's ρ, and McDonald's ω coefficients were used. Values over 0.70 are deemed satisfactory according to the standards established by Hair et al. (2017) and Nunnally and Bernstein (1994). Table 3 shows that all the constructs exceeded this level. With respect to the coefficient of determination (R^2), the values indicate that PE, EE, SI, ES, TS, PA, and AI together explain 71.5% of the variation in USAI. USAI explains 78.2% of the variation in PETH. Additionally, USAI accounts for 65.2% of the variation in TC.

The Fornell and Larcker (1981) criterion was employed to assess discriminant validity. Discriminant validity is determined by the criterion that the square root of the AVE, represented by the values on the diagonal, must exceed the correlations with other constructs, indicated

Table 3
Quality testing of the measurement model.

Contruct	ρ de Jöreskog	ρ de Dijkstra-Henseler	Coeficiente ω	R^2	PE	EE	SI	ES	TS	PA	AI	USAI	PETH	TC	HTMT
PE	0.823	0.824	0.813	–	**0.873**										0.556
EE	0.882	0.894	0.881	–	0.646	**0.834**									0.437
SI	0.801	0.818	0.825	–	0.599	0.678	**0.849**								0.637
ES	0.859	0.866	0.867	–	0.341	0.760	0.678	**0.762**							0.456
TS	0.834	0.839	0.832	–	0.542	0.562	0.665	0.563	**0.789**						0.387
PA	0.588	0.858	0.726	–	0.462	0.652	0.562	0.489	0.451	**0.932**					0.469
AI	0.895	0.831	0.748	–	0.456	0.745	0.679	0.456	0.561	0.652	**0.879**				0.643
USAI	0.834	0.821	0.834	0.715	0.672	0.762	0.698	0.672	0.641	0.757	0.560	**0.8654**			0.612
PETH	0.854	0.843	0.827	0.782	0.752	0.462	0.678	0.624	0.434	0.545	0.491	0.649	**0.790**		0.498
TC	0.789	0.779	0.780	0.652	0.562	0.567	0.682	0.532	0.542	0.672	0.658	0.575	0.641	**0.781**	0.541

by the values off the diagonal within the same row and column. An examination of the data in Table 3 clearly reveals that all the constructs satisfy this criterion. Furthermore, the heterotrait−monotrait ratio (HTMT) was employed, revealing that all the constructs presented values less than 0.85 (Rasoolimanesh, 2022, pp. 1–8), thereby reinforcing the assertion that the measurement instrument maintains discriminant validity.

The indices that assess the goodness-of-fit of a measurement model are essential for evaluating its convergent validity (Farhi et al., 2023). Hair (2009) posits that these criteria serve as essential benchmarks for researchers to evaluate the degree to which the observed values align with the anticipated values. Table 4 presents the goodness-of-fit indices for the measurement model, indicating that the standardized root mean square residual (SRMR) and RMSEA values are less than 0.85, thereby meeting the criterion set forth by Sun (2005). For the CFI and TLI criteria, the measurement model achieved values greater than 0.90, meeting the threshold proposed by Fábregas, Ardura, and Artola (2018). The NFI, however, failed to satisfy this need. According to Escobedo Portillo, Hernández Gómez, Estebané Ortega, and Martínez Moreno (2016), the model has an adequate fit when the chi-square/degrees of freedom ratio (χ^2/df) falls between 1 and 3. Finally, the GFI value of 0.966 meets the requirements of Escobedo Portillo et al. (2016), who state that a value greater than 0.80 is deemed appropriate.

4.2. Testing the hypotheses of the structural model

According to Hair (2009) and Kelcey, Cox, and Dong (2021), the direction and values of the paths of the links between the exogenous and endogenous variables in the study can be found via path analysis. Analysis of key results, including standardized coefficients (β), p values, confidence intervals and effect sizes (f^2), is presented in Table 5 and Fig. 2. First, H2 revealed a significant negative effect of EE on USAI ($\beta = -0.237^*$, $p = 0.049$, $f^2 = 0.031$). This finding indicates that greater perceived effort reduces the likelihood of adopting AI models in academic settings. The effect size is medium, suggesting that perceived difficulty serves as a moderately influential barrier to adoption. On the other hand, H3 showed that SI has a significant positive effect on USAI ($\beta = 0.195^*$, $p = 0.034$, $f^2 = 0.02$), confirming that social and institutional support promotes AI use. The effect size is small, reflecting a limited but relevant contribution. Additionally, H4 revealed a significant positive effect of ES on USAI ($\beta = 0.609^{**}$, $p = 0.009$, $f^2 = 0.103$), highlighting the importance of confidence in the ability to integrate AI into educational practices. The effect size is medium, indicating a considerable impact on the utilization of AI models. Moreover, H7 showed that AI has the strongest influence on USAI ($\beta = 0.782^{***}$, $p < 0.001$, $f^2 = 0.451$), underscoring the fundamental role of ethical considerations in the adoption of these technologies. The effect size is large, emphasizing its predominant impact on the model.

H8 revealed that USAI significantly affects TC ($\beta = 0.273^{***}$, $p < 0.001$, $f^2 = 0.074$), indicating that the use of AI shapes teachers' concerns. The effect size is medium, implying a significant influence on this construct. Finally, H9 demonstrated that USAI has a notable positive effect on PETH ($\beta = 0.556^{***}$, $p < 0.001$, $f^2 = 0.392$), suggesting that the practical use of AI fosters greater ethical awareness and reflection. The effect size is large, revealing a deep connection between AI use and ethical perceptions.

For the unsupported hypotheses, H1 did not show a significant effect of PE on USAI ($\beta = 0.023$, $p = 0.449$, $f^2 < 0.02$), suggesting the limited relevance of this factor in the studied context. Similarly, H5 and H6 also failed to achieve significance, as TS ($\beta = 0.013$, $p = 0.475$, $f^2 = 0.006$) and PA ($\beta = 0.081$, $p = 0.212$, $f^2 = 0.003$) had minimal or no influence on AI adoption.

In summary, the results highlight the importance of ethical factors (AIs), educational self-efficacy (ES), and social influence (SI) as key drivers in the adoption of AI models in academic settings. Effect sizes range from small to large, reflecting varying degrees of influence among predictors. These findings underscore the need for interventions aimed at facilitating AI use, addressing ethical concerns, and fostering supportive environments to encourage its responsible integration into the educational field.

5. Discussion

The main objective of this study was to analyze the predictors of USAI among academic researchers. The findings revealed complex patterns of influence that both align with and challenge existing theoretical frameworks.

The results demonstrated that AI emerged as the strongest predictor of USAI ($\beta = 0.782^{***}$, $f^2 = 0.451$), with a large effect size that substantially exceeded Cohen's threshold of 0.35. This dominant influence aligns with recent studies highlighting ethical considerations in AI adoption (Farina & Stevenson, 2024; Song, 2024), but the magnitude of the effect suggests that ethical concerns may be even more central to adoption decisions than previously recognized, particularly in emerging academic contexts.

ES had the second strongest positive influence ($\beta = 0.609^{**}$, $f^2 = 0.103$), with a medium effect size. This finding extends previous research on academics' confidence in technology integration (Sharma

Table 4
Goodness-of-fit and goodness-of-fit tests.

Indicator	Estimated model	Threshold	Author	Decision
RMSEA	0.048	<0.85	Sun (2005)	Acceptable
SRMR	0.048	<0.85	Sun (2005)	Acceptable
CFI	0.938	>0.90	Fábregas et al. (2018)	Acceptable
TLI	0.928	>0.90	Fábregas et al. (2018)	Acceptable
NFI	0.862	>0.90	Fábregas et al. (2018)	Not acceptable
χ2/df	1.70	Entre 1 y 3	Escobedo Portillo et al. (2016)	Acceptable
GFI	0.966	>0.80	Escobedo Portillo et al. (2016)	Acceptable

Table 5
Results of hypothesis testing.

Regression coefficients									
								95% Confidence Interval	
Result		Predictor	β	f^2	Error Típico	Z value	p value	Lower	Upper
H_1	USAI	PE	0.023	2.152×10^{-4}	0.182	0.129	0.449	−0.348	0.369
H_2		EE	−0.237*	0.031	0.168	−1.412	0.049*	−0.580	0.081
H_3		SI	0.195*	0.02	0.135	1.446	0.034*	−0.050	0.478
H_4		ES	0.609**	0.103	0.259	2.349	0.009**	0.138	1.138
H_5		TS	0.013	0.006	0.212	0.063	0.475	−0.460	0.388
H_6		PA	0.081	0.003	0.101	0.800	0.212	−0.110	0.288
H_7		AI	0.782***	0.451	0.096	0.358	<0.001***	0.148	0.835
H_8	TC	USAI	0.273***	0.074	0.075	3.643	<0.001***	0.142	0.401
H_9	PETH	USAI	0.556***	0.392	0.054	10.238	<0.001***	0.442	0.657

Note. ***β*** = path coefficient; SE = standard deviation; ***p < 0.001; **p < 0.01; *p < 0.05; Interpretation of effect size according to Cohen (1992): small $f^2 < 0.02$; medium $f^2 < 0.15$; large $f^2 \geq 0.35$.

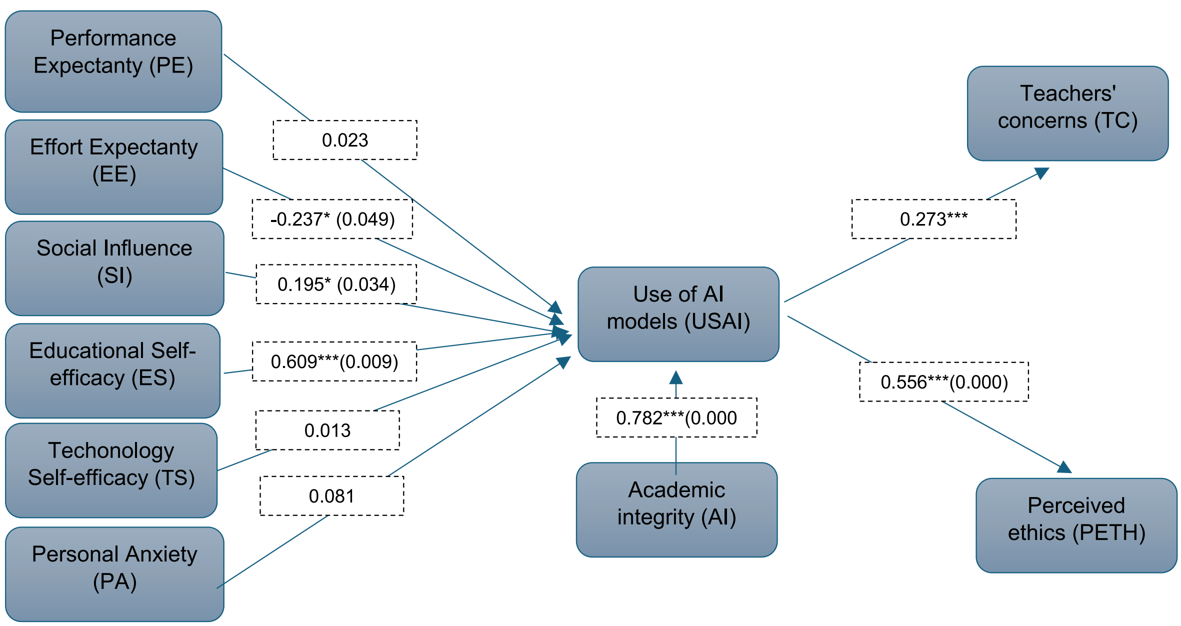

Fig. 2. Structural model solved.

et al., 2024; Y. Wang et al., 2021), suggesting that pedagogical confidence may be more crucial than technical skills in predicting AI adoption. The medium effect size indicates that while significant, its influence is notably less than that of ethical considerations.

SI demonstrated a significant but smaller effect (β = 0.195*, f^2 = 0.02), barely meeting Cohen's threshold for small effects. While this finding supports previous findings about peer influence (Strzelecki & ElArabawy, 2024; Supianto et al., 2024), the relatively small effect size suggests that in the Peruvian academic context, institutional and peer pressure play a more modest role than individual ethical and educational considerations do.

EE showed an unexpected negative influence (β = −0.237*, f^2 = 0.031) with a small to medium effect size, contradicting some previous research (Dahri et al., 2024; Duong et al., 2023). This finding suggests that in the context of AI adoption, perceived difficulty might actually encourage rather than discourage use, possibly due to a recognition of AI complexity and the need for careful implementation.

Perhaps most surprisingly, PE had no significant effect (β = 0.023, p = 0.449, $f^2 < 0.02$), in sharp contrast with previous studies where it was a key predictor (Altememy, Mohammed, et al., 2023; Strzelecki & ElArabawy, 2024). This unexpected finding, along with the minimal effect size, suggests that in the Peruvian academic context, the potential performance benefits of AI are not primary drivers of adoption. Similarly, TS has a negligible influence (β = 0.013, f^2 = 0.006), challenging assumptions about the importance of technical confidence (Chou et al., 2022; Salhieh & Al-Abdallat, 2022).

The impact of USAI on TC was significant but moderate (β = 0.273***, f^2 = 0.074), suggesting that actual AI use shapes faculty concerns differently than anticipated by previous research (Abdelaal & Al Sawi, 2024; Meza et al., 2024). More notably, USAI had a strong influence on PETH (β = 0.556***, f^2 = 0.392), with an effect size approaching the threshold for large effects. This robust relationship, supported by previous studies (Dolunay & Temel, 2024; Zhu et al., 2024), suggests that practical experience with AI significantly shapes ethical awareness.

These findings reveal a more nuanced picture of AI adoption in academic settings than previously understood. The predominance of AI and ES over traditional technology acceptance factors suggests the need to reconceptualize how we understand AI adoption in academic contexts, particularly in emerging economies. The minimal influence of PE and TS, which are traditionally central to technology adoption models, indicates that the unique characteristics of AI and the academic context may require new theoretical frameworks.

The effect sizes observed provide crucial insights for prioritizing interventions. The large effect of AI (f^2 = 0.451) suggests that ethical frameworks and guidelines should be the primary considerations in AI implementation strategies. The medium effect of ES ($f^2 = 0.103$) indicates that pedagogical training may be more valuable than technical training, whereas the small effect of SI ($f^2 = 0.02$) suggests that institutional pressure alone may be insufficient to drive adoption.

This pattern of results may reflect particular characteristics of the Peruvian academic context, where ethical considerations and pedagogical confidence appear more influential than do technical or performance factors. These findings suggest the need for culturally sensitive approaches to AI implementation in academic settings, particularly in emerging economies where institutional and cultural contexts may differ significantly from those of more studied environments.

5.1. Discussion of theoretical and practical implications

This study offers significant theoretical contributions by extending the UTAUT2 model through the incorporation of AI and PETH as predictors of AI adoption in research settings. While UTAUT2 has traditionally focused on technological and social factors, our findings suggest that in contexts involving ethically sensitive technologies such as AI, the model requires substantial modification. The strong effect of AI ($f^2 = 0.451$) and the significant influence of USAI on PETH ($f^2 = 0.392$) indicate that ethical considerations may be more fundamental to technology adoption than previously recognized in UTAUT2 frameworks. This suggests the need for a theoretical reorientation that places ethical considerations at the core, rather than the periphery, of technology adoption models in academic contexts.

Furthermore, our findings challenge traditional UTAUT2 assumptions by demonstrating the nonsignificance of PE and the minimal impact of TS. These unexpected results suggest that when dealing with ethically complex technologies such as AI, conventional predictors may be less relevant than ethical and educational factors are. This theoretical insight extends beyond AI to potentially inform our understanding of adoption patterns for other ethically sensitive technologies in academic settings.

The bidirectional relationship between USAI and PETH represents another important theoretical contribution. This finding suggests a dynamic process where ethical awareness is not just a precursor to adoption but is also shaped by direct experience with the technology. This recursive relationship challenges linear adoption models and suggests the need for more complex theoretical frameworks that can account for such feedback loops in technology adoption processes.

From a practical perspective, these findings suggest several specific interventions for higher education institutions. First, institutions should develop comprehensive ethics-first policy frameworks that include clear guidelines for AI use in different research contexts, establish ethical review processes, and create transparent reporting requirements for AI use in publications. These policies should be supported by robust monitoring systems that ensure compliance while promoting responsible innovation.

Second, institutions should implement targeted training programs that extend beyond technical skills to address the ethical dimensions of AI use. These programs should combine theoretical understanding with practical application, focusing on discipline-specific scenarios and real-world ethical challenges. The development of peer mentoring systems can facilitate knowledge sharing and promote best practices in ethical AI adoption.

Third, universities should establish robust institutional support structures for ethical AI implementation. This includes creating dedicated AI ethics committees at the departmental level and support centers that can provide guidance on ethical considerations in AI-assisted research. Regular ethical audits of AI use in research can help maintain high standards of academic integrity while identifying areas for improvement.

In terms of educational development initiatives, our findings suggest that institutions should focus on enhancing ES through programs that combine practical experience with ethical reflection. This could involve creating collaborative learning communities where researchers can share experiences and insights about ethical AI use. Regular workshops that integrate hands-on AI training with ethical discussions can help develop both technical competence and ethical awareness.

However, these practical implications must be considered within appropriate contextual boundaries. Given our study's focus on Peruvian universities and nonprobabilistic sampling, implementation strategies may need adaptation for different cultural and institutional contexts. The strong influence of ethical considerations might be particularly pronounced in our sample's cultural context, suggesting the need for culturally sensitive implementation approaches.

The relationship between USAI and PETH has specific practical implications for how institutions approach AI training. Rather than focusing solely on technical skills, our findings suggest that hands-on experience with AI tools, coupled with ethical reflection, might be more effective in developing responsible adoption practices. This could involve integrating regular ethics workshops with practical training, discussing case studies of ethical AI use in research, and facilitating reflection sessions on AI experiences and their ethical implications.

These implications provide a foundation for developing comprehensive AI adoption strategies in academic settings while acknowledging the need for contextual adaptation and further validation in diverse institutional environments. The emphasis on ethical considerations and educational self-efficacy suggests that successful AI implementation requires a holistic approach that addresses both the technical and ethical dimensions of technology adoption.

5.2. Presentations of limitations and suggestions for future studies

This study presents several methodological limitations that warrant careful consideration and provide opportunities for future research. The cross-sectional nature of our study constrains our understanding of how academics' perceptions and behaviors regarding AI use evolve over time, which is particularly relevant given the rapid advancement of AI technologies and changing institutional policies. This temporal limitation is especially significant, as the relationship between ethical awareness and AI adoption likely develops dynamically over time.

The reliance on self-reported measures represents another significant limitation. This approach may introduce social desirability bias, particularly concerning ethical considerations and academic integrity. The participants might have overstated their ethical compliance or understated their concerns about AI adoption. This limitation is particularly relevant for constructs such as AI and PETH, where social expectations might influence responses.

Our study's nonprobabilistic sampling approach and demographic composition present notable limitations. The predominance of early-career researchers may have led to the underrepresentation of senior academics, potentially skewing our understanding of how experience levels influence AI adoption. Furthermore, the concentration of participants from certain institutional types might not fully capture the diversity of academic contexts, particularly with respect to access to AI resources and institutional support structures.

The geographically constrained focus on Peruvian universities, while providing valuable insights into an emerging economy context, limits the generalizability of our findings. Different cultural contexts, technological infrastructures, and institutional frameworks might significantly alter the relationships we observed between our constructs. This limitation becomes particularly relevant when considering how ethical frameworks and academic practices vary across different cultural and institutional settings.

A significant limitation involves the lack of differentiation between various AI models and their specific applications in research contexts. Our study treated AI as a uniform technology, whereas different tools (such as text generation, data analysis, or research assistants) might elicit different adoption patterns and ethical considerations. This generalization may mask important variations in how different AI applications influence academic work.

The absence of an institutional policy context represents another limitation. Our study did not explicitly account for existing institutional guidelines or ethical frameworks that might influence AI adoption decisions. This omission limits our understanding of how organizational policies mediate the relationship between individual perceptions and adoption behaviors.

Furthermore, while our statistical analysis identified significant relationships between constructs, the mechanisms underlying these relationships require further investigation. The quantitative approach, while robust, may not fully capture the nuanced ways in which ethical considerations interact with traditional technology acceptance factors.

To address these limitations, future research could employ longitudinal designs to track changes in adoption patterns and ethical perceptions over time. Mixed-method approaches, which combine quantitative surveys with qualitative methods such as in-depth interviews and observational studies, could provide richer contextual understanding. Cross-cultural validation studies comparing AI adoption patterns across different academic cultures would enhance the generalizability of our findings.

Future studies should also consider more granular analyses of how adoption factors vary across different AI applications and academic disciplines. This could include developing specialized measurement instruments for specific AI use contexts and examining how institutional policies influence adoption patterns. Additionally, investigating the relationship between AI adoption and research quality through bibliometric analyses could provide valuable insights into the practical impacts of AI integration in academic research.

From a methodological perspective, future research should employ more sophisticated analytical techniques, including multilevel modeling to account for institutional effects, latent class analysis to identify adoption patterns, and social network analysis to better understand peer influence mechanisms. Qualitative comparative analysis could help identify combinations of factors leading to successful AI adoption, whereas experimental studies could examine the impact of different training approaches.

These future research directions would not only address our study's limitations but also contribute to a more comprehensive understanding of AI adoption in academic settings, particularly focusing on the ethical and cultural dimensions that our findings suggest are crucial.

6. Conclusions

This study makes several significant contributions to both the academic literature and practical applications in higher education regarding AI adoption. First, our findings provide compelling evidence that traditional technology acceptance models need significant modification when applied to AI in academic contexts. The strong predictive power of AI represents a crucial theoretical advancement, demonstrating that ethical considerations are not merely peripheral factors but fundamental drivers of AI adoption in research settings. These findings challenge conventional technology acceptance frameworks and suggest the need for more ethically centered models when studying AI adoption.

Second, our research reveals the critical role of ES in AI adoption, surpassing traditional technical factors. This finding advances our understanding of how academics approach AI integration, suggesting that confidence in pedagogical application is more crucial than technical expertise. This insight has significant implications for how institutions approach AItraining and support programs, indicating a need to focus on educational integration rather than purely technical instruction.

Third, the unexpected negative influence of EE and the non-significance of PE and TS challenge fundamental assumptions about technology adoption in academic settings. These findings suggest that when dealing with sophisticated technologies such as AI, traditional barriers to adoption may operate differently than previously theorized. This represents a significant contribution to the literature on technology acceptance in complex professional contexts.

Fourth, the strong bidirectional relationship between USAI and PETH reveals a dynamic interaction between practice and ethical awareness that has not been previously documented in the literature. This finding suggests that ethical understanding of AI is not just a precursor to adoption but is actively shaped by practical experience, offering new insights into how ethical awareness develops in technological contexts.

From a practical perspective, our findings provide a clear direction for institutional policies and practices. The predominance of ethical considerations suggests that universities should prioritize the development of robust ethical frameworks for AI use. The significance of ES indicates that professional development programs should focus on building confidence in integrating AI into educational and research practices, whereas the modest role of SI suggests that institutional support should focus on enabling rather than mandating AI adoption.

In the broader context of higher education, this study demonstrates that successful AI integration requires a more nuanced approach than traditional technology implementation does. The complex interplay between ethical considerations, educational confidence, and practical experience suggests that institutions need to develop comprehensive, ethically grounded strategies for AI adoption that go beyond technical training and infrastructure development.

These findings have particular relevance for emerging economies and developing educational systems, where the balance between technological advancement and ethical considerations may be especially crucial. While acknowledging the study's limitations, our results provide a strong foundation for understanding how academic institutions can promote responsible and effective AI adoption while maintaining high standards of academic integrity.

This research opens new avenues for investigating how educational institutions can balance technological innovation with ethical considerations and academic values. It provides a framework for understanding AI adoption that recognizes the unique challenges and opportunities presented by these technologies in academic contexts while emphasizing the importance of maintaining ethical standards and educational effectiveness in an increasingly AI-enabled academic environment.

CRediT authorship contribution statement

Benicio Gonzalo Acosta-Enriquez: Writing – review & editing, Investigation, Conceptualization. **Marco Arbulu Ballesteros:** Writing – review & editing, Investigation, Formal analysis. **César Robin Vilcapoma Pérez:** Writing – original draft, Investigation, Conceptualization. **Olger Huamaní Jordan:** Writing – original draft, Investigation, Conceptualization. **Joseph Anibal Martin Vergara:** Formal analysis, Conceptualization. **Rafael Martel Acosta:** Writing – review & editing, Formal analysis. **Carmen Graciela Arbulu Perez Vargas:** Writing – review & editing, Conceptualization. **Julie Catherine Arbulú Castillo:** Project administration, Formal analysis.

Availability of data and material

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

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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