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Review article

Acceptance of artificial intelligence in university contexts: A conceptual analysis based on UTAUT2 theory

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A R T I C L E I N F O

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A B S T R A C T

This systematic review examined, through the UTAUT2 model, the factors influencing the acceptance of artificial intelligence (AI) applications in university contexts. A total of 50 scientific texts published between 2018 and 2023 were analyzed and selected after a rigorous search of specialized databases. These findings confirm the versatility of UTAUT2 in elucidating technological adoption processes in higher education. Performance expectancy and hedonic motivation emerged as significant predictors of intentions and effective use among students, faculty, and administrative staff. Among students, perceived ease of use and social influence were also relevant. The analysis revealed differences in adoption patterns between STEM and non-STEM disciplines and between public and private institutions. Despite widespread positive perceptions of AI's potential, barriers such as distrust and lack of knowledge persist. The research also identified moderating and mediating factors, such as prior technology experience and technological self-efficacy. These results have important implications for the implementation of AI in higher education, suggesting the need for differentiated approaches according to the characteristics of each group and institutional context. It is recommended to develop strategies that address the identified barriers and leverage facilitators, with an emphasis on training, ethical design, and contextual adaptation of AI applications. Future research should explore the longitudinal evolution of these factors and examine AI adoption in non-STEM disciplines in greater depth.

1. Introduction

The unified theory of acceptance and use of technology 2 (UTAUT2) is an established model for examining the adoption of digital innovations in educational environments [1,2]. It is widely used to understand the adoption and use of technology [3–5], comprising constructs such as performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price

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value, habit, and behavioral intention [4,6]. UTAUT2 is robust across most dimensions, except for parsimony, due to its complex model [5]. It has extensive usage in information systems and beyond, with over 6000 citations [5,7], explaining 75 % of behavioral intentions related to technology adoption [6]. However, some limitations of UTAUT2 include the lack of longitudinal research, the controversial role of certain factors, and the need to verify actual user behavior with objective data [3,5]. Despite criticisms of its complex structure and the controversial role of certain factors [4], its versatility and utility are evident in various applications studying the use of learning management systems, e-learning, and virtual reality, among other technological solutions [8,9].

The predictive potential of UTAUT2 lies in its fundamental constructs, which explain behavioral intentions and the effective use of technologies by students and faculty, such as performance expectancy, effort expectancy, social influence, facilitating conditions, and hedonic motivation [10]. Empirical research corroborates the significant impact of these factors on the acceptance of digital educational platforms [9]. Additionally, the cross-cultural applicability of UTAUT2 has been demonstrated in diverse contexts, such as universities in India and Vietnam [10,11], confirming its utility in elucidating how individual and contextual elements shape technological adoption, from MOOCs to mobile applications [10]. Overall, this theoretical-analytical model provides an invaluable lens for researchers and educational stakeholders to identify ways to optimize the meaningful incorporation of emerging digital technologies in the service of learning.

In the specific context of university education, the UTAUT2 theory has proven to be an increasingly useful analytical framework [1,2]. Recent studies have employed it to evaluate the acceptance of various technological innovations, ranging from the mobile internet for faculty [12] to perceptions of artificial intelligence among future teachers [13]. Correspondingly, research adopting UTAUT2 in this domain has been increasing exponentially in recent years [4,14]. Beyond analyzing technology adoption among professors, this model allows for elucidating and predicting usage responses of digital platforms among undergraduate and graduate students [1,2].

The findings corroborate that core UTAUT2 constructs such as performance expectancy, effort expectancy, and hedonic motivation also strongly influence higher education [2]. The model's adaptability is evidenced in extensions incorporating variables such as teacher traits, external incentives, and organizational culture, achieving greater predictive precision in complex educational environments [15]. Altogether, UTAUT2 represents an indispensable lens for administrators and educators to identify optimal avenues for integrating technology in university learning services.

Recent research has confirmed the influence of central UTAUT2 constructs, such as performance expectancy, effort expectancy, facilitating conditions, and hedonic motivation, on the acceptance and adoption of digital platforms in higher education environments [1,2]. The model's flexibility to adapt to complex educational settings is evident in extensions incorporating variables derived from teacher characteristics, external incentives, and organizational culture. These factors significantly enhance universities' ability to predict their technological usage intentions and behaviors [15].

Simultaneously, cutting-edge technologies such as artificial intelligence (AI) are profoundly transforming teaching and learning methods in this context [16]. While they introduce challenges related to new digital competencies and pedagogies, they also offer opportunities through personalization, motivation, and learning support [17]. Despite promising signs of their educational benefits, more empirical evidence is needed [18]. However, their strategic implementation could enhance student learning and experiences [19]. Examining the factors influencing AI acceptance through the UTAUT2 model could guide the effective integration of these emerging technologies to strengthen university educational processes.

The UTAUT2 theory has been applied in several studies on technology adoption in higher education, revealing that constructs such as performance expectancy, effort expectancy, facilitating conditions, and hedonic motivation influence the usage responses of digital innovations among students and faculty [1]. Additionally, pedagogical approaches such as SAMR, TPACK, and TAM could optimize AI integration, with promising indications of their potential to improve learning [18]. However, there is still a lack of compelling empirical evidence on the concrete impacts of AI on university educational processes and outcomes [20]. Effective integration will also require adapting programs to develop 21st-century competencies in students and faculty [16]. In sum, in-depth analysis of the factors determining AI acceptance using the UTAUT2 model will guide optimal implementations to foster innovation in contemporary university teaching and learning practices.

The purpose of this research was to analyze the factors influencing the acceptance of artificial intelligence applications in higher education environments. To achieve this goal, a systematic review of contemporary literature was conducted using the UTAUT2 model as a conceptual framework to examine the perceptions, attitudes, and adoption responses of these emerging technologies among university students, faculty, and administrative staff. Additionally, two specific objectives were outlined: to compare differences in the factors predicting AI adoption among students, faculty, and administrative staff in higher education institutions and to categorize the most common perceptions and attitudes toward AI applications in university settings according to findings in the reviewed literature.

This study was justified by the rapid advancement of AI in various spheres, including the transformation of university education. AI was anticipated to substantially modify how higher education is delivered, managed, and conceived in the coming years. However, there is still limited research on how AI specifically impacts concrete educational practices and processes within universities.

Therefore, this systematic review comprehensively analyzes the elements involved in the incorporation of AI platforms among different university stakeholders. The UTAUT2 model has shown great utility in elucidating technological adoption in this context. Thus, its application here provides an updated overview of facilitating and hindering factors, informing the formulation of AI initiatives that genuinely add pedagogical value to contemporary higher education institutions.

2. Materials and methods

This research employs a qualitative methodology based on the documentary analysis of scientific literature. A critical and comprehensive synthesis of existing knowledge is carried out, taking into account various sources, such as research articles, which serve to validate theoretical assumptions about the acceptance of artificial intelligence in university contexts.

Four databases were selected for this review: Scopus, Web of Science, ScienceDirect and ProQuest. This selection was based on the following criteria:

1. Scopus and Web of Science: These databases were considered fundamental because of their broad coverage of peer-reviewed academic literature in the social sciences and technology. Scopus, in particular, offers broader coverage of international journals (Mongeon & Paul-Hus, 2016).
   ScienceDirect: This was included to capture open access articles and gray literature that might not be indexed in Scopus or Web of Science.
3. ProQuest: Selected to include relevant doctoral theses and dissertations that could provide additional insights.

We considered that the combination of these four databases provided sufficiently broad and diverse coverage for the purposes of this review.

2.1. *PRISMA flow chart*

The methodology employed in this study was based on a systematic literature review following the PRISMA flow diagram guidelines (see Fig. 1). The article selection process consisted of four main stages:

Identification: An initial search was conducted in four databases (Scopus, Web of Science, ScienceDirect, and ProQuest), yielding a total of 5180 potentially relevant articles.

Screening: Filters were applied based on language (English and Spanish), thematic area (higher education and technology), and publication date (last 5 years), reducing the number of articles to 516.

Eligibility: The titles and abstracts of these 516 articles were reviewed using specific inclusion criteria. These criteria included a focus on AI adoption in higher education, the use of the UTAUT2 model or relevant extensions, and the use of empirical studies or systematic reviews. Studies that did not specifically focus on higher education or only mentioned AI or UTAUT2 without substantial analysis were excluded.

Inclusion: A total of 50 articles were selected for the final review (see Table 1). To mitigate potential biases, two researchers independently conducted the selection, discussion and resolution of any disagreements. Additionally, a manual search of the reference lists of the selected articles was performed to identify additional relevant studies.

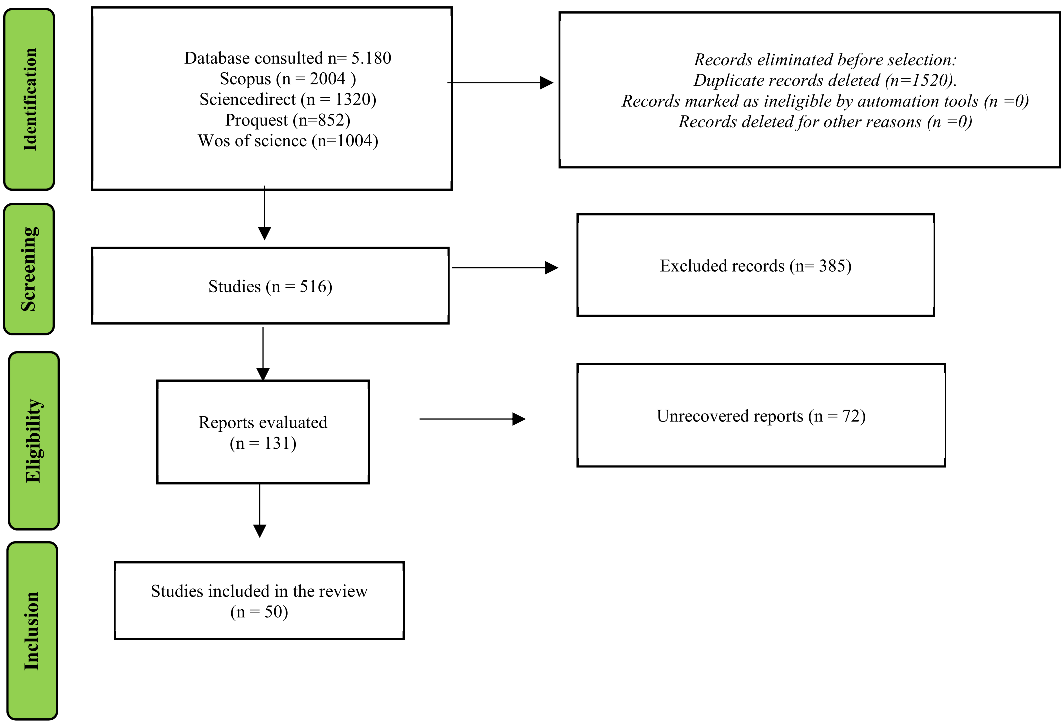

Fig. 1. PRISMA flow chart.

Table 1
Number of documents consulted.

Source	Number of files	Key words
Scopus	19	'acceptance of artificial intelligence', "UTAUT2" and "adoption of educational technology".
ScienceDirect	15	'acceptance of artificial intelligence', "UTAUT2" and "adoption of educational technology".
ProQuest	10	'acceptance of artificial intelligence', "UTAUT2" and "adoption of educational technology", "acceptance of artificial intelligence", "UTAUT2" and "adoption of educational technology".
Web Of Science	06	'acceptance of artificial intelligence', "UTAUT2" and "adoption of educational technology".
TOTAL	50	

2.2. *Data analysis procedure*

The data analysis procedure was conducted systematically and rigorously. Initially, the bibliographic information of the articles identified in the selected databases was exported in RIS format. This file included key data such as citation information, bibliographic details, abstracts, and keywords of each study.

Subsequently, the researchers imported this RIS database into the open-access software VOSviewer, a tool specialized in bibliometric analysis. In the main interface of the software, a step-by-step process was followed to create a map based on the bibliometric data. This process involved selecting the option to create a new map and then specifying that the analysis would be performed on the data contained in the previously imported RIS file.

For the specific analysis, a co-occurrence analysis was chosen, focusing on two main units of analysis: keywords and the institutions of the authors. This choice allowed for examining both the predominant themes in the literature and the collaboration networks among institutions.

The result of this analysis materialized in two key visualizations: Figs. 2 and 3. These graphical representations offer a visual perspective of the interconnections between key concepts and institutional collaboration in the field of study, allowing for the identification of trends, thematic clusters, and collaboration networks in research on the adoption of artificial intelligence in higher education.

2.3. *Codification process*

The coding process employed in this study was meticulous and systematic, beginning with the development of an initial coding scheme. This scheme incorporated not only the constructs of the UTAUT2 model but also additional factors identified as relevant for AI adoption in higher education settings. These factors included performance expectancy, effort expectancy, hedonic motivation, security, trust, behavioral intention, habit, price value, facilitating conditions, ease of use, and social influence.

Researchers began the process with an exhaustive reading and annotation of the 50 selected scientific texts published between 2018 and 2023. During this phase, special attention was given to findings related to the versatility of UTAUT2 in higher education contexts. Subsequently, open coding was conducted to identify positive perceptions about the potential of AI, as well as barriers such as distrust

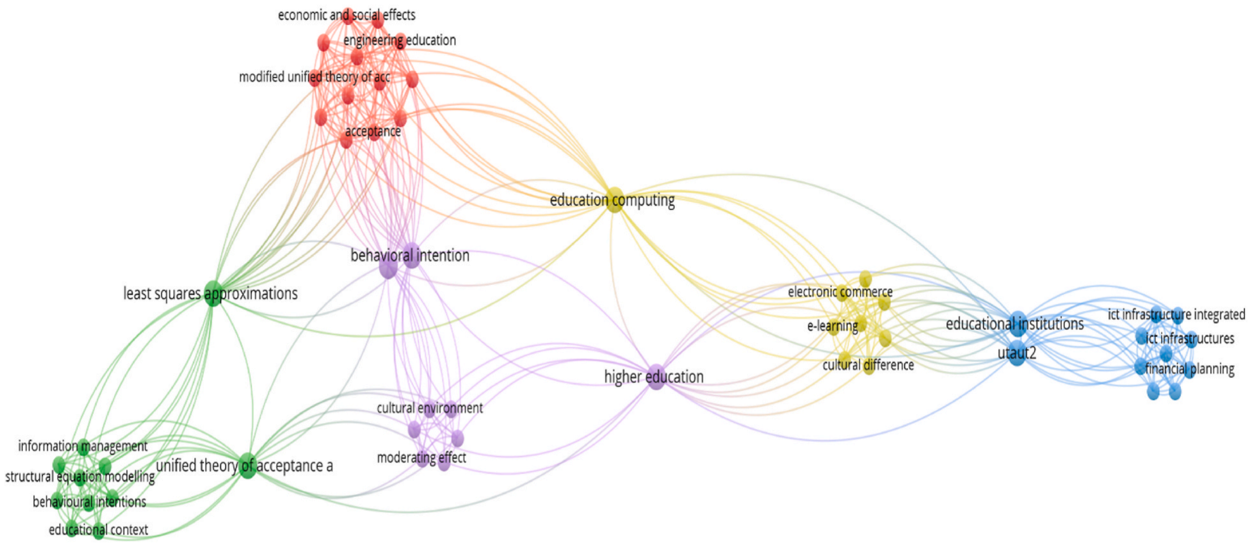

Fig. 2. Bibliometric map according to keywords of studies on technology and education centered on the UTAUT2 model.

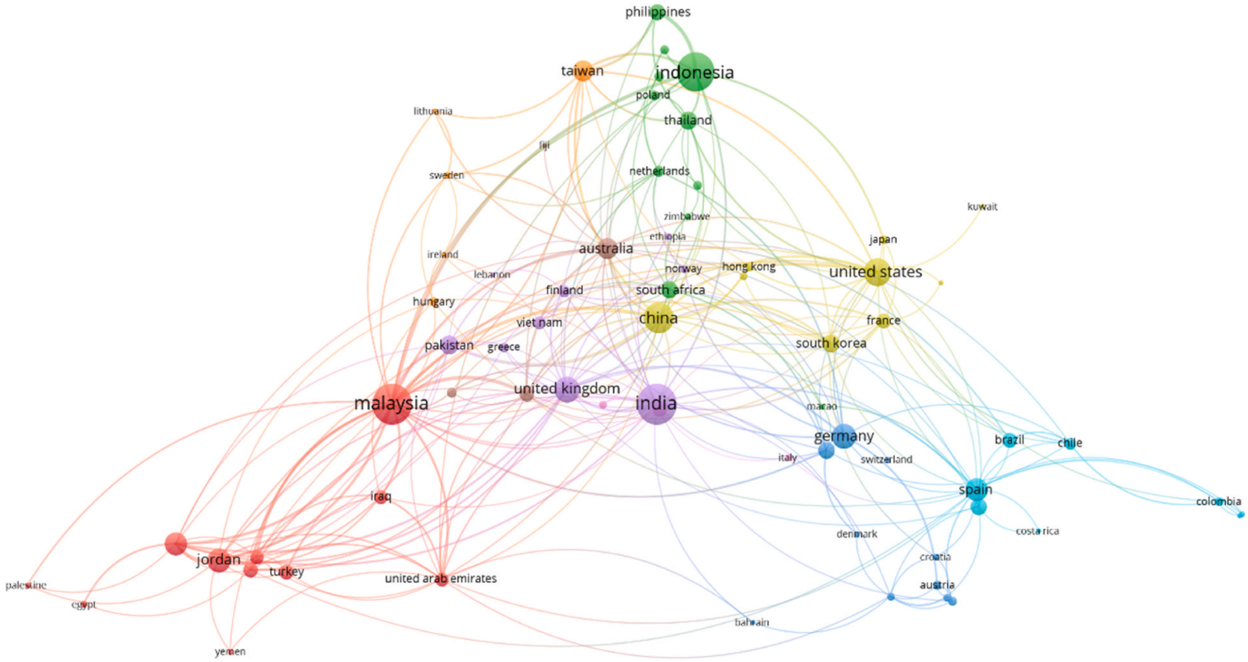

Fig. 3. Bibliometric map of countries' research collaboration on the topic.

and lack of knowledge about AI.

In the initial coding phase, researchers grouped codes related to facilitators and obstacles contextualized through UTAUT2 and identified relationships between factors predicting AI adoption in different university groups. Selective coding allowed for the refinement of the main categories, such as "factors influencing AI acceptance" and "perceptions and attitudes toward AI," and the integration of findings on the cross-cultural applicability of UTAUT2 in various university contexts.

A frequency analysis was conducted to determine the occurrence of key factors, such as performance expectancy, hedonic motivation, perceived ease of use, and social influence, to identify the most significant predictors for each group: students vs. faculty, undergraduates vs. graduates, STEM vs. non-STEM disciplines, and public vs. private institutions.

Additionally, figures were created to illustrate keywords and country collaborations in research on AI acceptance and UTAUT2, incorporating new elements from the VOSviewer bibliometric map presented in Figs. 2 and 3.

The coding scheme was iteratively refined based on emerging findings about the application of UTAUT2 in educational AI contexts, and text samples were recoded to ensure consistency in the interpretation of constructs. The coded findings were integrated into a narrative synthesis addressing the specific objectives of the study, comparing differences in factors predicting AI adoption among university groups and categorizing the most common perceptions and attitudes toward AI applications.

Finally, the researchers evaluated the theoretical and practical implications, coding findings related to the validation and extension of UTAUT2 in the context of AI in higher education and identifying practical implications for the implementation of AI in higher education institutions.

3. The results and discussion

Table 2 shows the results of the systematization of the studies consulted. Information such as title and year, methodology, sample, results and conclusions is presented.

Fig. 2 presents a VOSviewer bibliometric map depicting the interconnection between key terms in the literature related to technology and education, centered on the UTAUT2 model. Terms with large nodes such as "behavioral intention," "acceptance," and "e-learning" indicate their high frequency and centrality, suggesting that these are dominant themes in the analyzed studies. The connections between these nodes and others, such as "higher education" and "educational institutions", highlight a significant focus on how technology acceptance is integrated within the higher education domain. Differentiated colors symbolize specific thematic groups, revealing possible subdisciplines or approaches within the broader field of technology use in education. The density of connections between terms such as "education computing," "economic and social effects," and "engineering education" demonstrates the interdisciplinarity and relevance of social and economic factors in technological adoption in educational contexts.

From another perspective, the strong connection between STEM (red cluster) and AI adoption in higher education can be attributed to several factors. First, there is a natural affinity between STEM disciplines and AI, as both disciplines share technical and computational foundations. Additionally, students and faculty in these fields often possess greater digital literacy and familiarity with advanced technological concepts, facilitating the integration of AI into their educational practices. The direct applicability of AI in

Table 2
Systematization of studies consulted.

Title and year	Methodology	Sample	Results and conclusions
Huang C.-Y.; Yang M.-C.; Huang C.-Y [21]. "Empirical investigation of factors influencing consumer intention to use an artificial intelligence-powered mobile application for weight loss and health management"	Structural equation modeling	458 people	Habit was the most important independent variable for predicting user intention, followed by personal innovativeness, network externality and performance expectancy.
Gansser O.A.; Reich C.S [22]."A new acceptance model for artificial intelligence with extensions to UTAUT2: An empirical study in three segments of application".	PLS analysis methodology	21.841	All factors additional to the UTAUT2 model except safety play a relevant role in explaining the behavioral intention and use of AI products.
Xian X. [23], "Psychological factors in consumer acceptance of artificial intelligence in the leisure economy: a structural equation model"	Structural equation modeling methodology	560	Expected AI performance, social circle, enabling conditions, enjoyment of using AI, price value and user habitus significantly influence AI adoption.
Huang C.-Y.; Yang M.-C.; Huang C.-Y.; Chen Y.-J.; Wu M.-L.; Chen K.-W. [24], "A Chatbot-supported smart wireless interactive healthcare system for weight control and health promotion"	Methodology not specified	No sample specified	Interactive chatbot system for weight management and health promotion
Aswani R.; Ilavarasan P.V.; Kar A.K.; Vijayan S. [25], "Adoption of public WiFi using UTAUT2: An exploration in an emerging economy"	Regression analysis and Path analysis methodology.	257	Facilitating conditions, performance expectancy, effort expectancy, social influence, hedonic motivation, trust, individual characteristics, business intention and usage influence the acceptance of public Wi-Fi technology. Behavioral intention is largely explained by performance expectancy, hedonic motivation and trust.
Shanthana Lakshmi S.; Deepak Gupta [26] "The Smart Set: A Study on the Factors that Affect the Adoption of Smart Home Technology"	Ordered logistic regression methodology	148	Expectation of performance and testability along with reliability and technological attitude have a significant influence on users' adoption of smart home technology. Users' psychological risk and environmental concerns negatively influence residents' purchase intention.
Habibi A.; Muhaimin M.; Danibao B.K.; Wibowo Y.G.; Wahyuni S.; Octavia A. [27], "ChatGPT in higher education learning: Acceptance and use"	Partial Least Squares Structural Equation Modeling Methodology and Importance-Performance Analysis	1117	Facilitating conditions were the strongest determinant of behavioral intention to use ChatGPT and significantly predicted ChatGPT Use. Effort expectancy did not show a significant effect on behavioral intention. Importance-performance analysis showed that facilitating conditions had the most significant importance for behavioral intention, while behavioral intention was the most important determinant for ChatGPT Use.
Wang Y.; Zhang W. [28], "Factors Influencing the Adoption of Generative AI for Art Designing Among Chinese Generation Z: A Structural Equation Modeling Approach	Structural equation modeling methodology	326	UTAUT2 effort expectancy, price value and hedonic motivation positively influence the intention to use generative AI, while performance expectancy does not show a statistically significant effect. Optimism and creativity contribute significantly to performance expectancy, effort expectancy, price value and hedonic motivation.
Frank M.P.; George G. [29], "Pilot Study on Adoption and Usage of AI in Food Processing Industry by UTAUT2″	Questionnaire methodology and reliability testing	62	Test-retest reliability of the questionnaire according to Cronbach's Alpha of 0.874, McDonald's Omega within the range of 0.80–0.90 and interrater reliability within the range of moderately acceptable scores of 50–75 %.
Xian X. [23], "Psychological factors in consumer acceptance of artificial intelligence in leisure economy: A structural equation model"	structural equation modeling methodology	560	Expected AI performance, social circle, facilitating conditions, enjoyment of using AI, price value and user habit significantly influence AI adoption.
Çalışkan G.; Yayla İ.; Pamukçu H. [30], "The use of augmented reality technologies in tourism businesses from the perspective of UTAUT2″	Interview methodology and analysis with MAXQDA	No sample specified	The usefulness and potential of augmented reality in tourism businesses according to app developers and accommodation managers.
Tavares J.; Goulao A.; Oliveira T. [31], "Electronic health record portals adoption: Empirical model based on UTAUT2″,	Structural equation modeling	271	Expected performance, effort expectancy, social influence, facilitating conditions, value pricing, habitus and hedonic motivation significantly determined intention to adopt electronic health record portals.

(continued on next page)

Table 2 (*continued*)

Title and year	Methodology	Sample	Results and conclusions
Alhwaiti M. [32], “Acceptance of Artificial Intelligence Application in the Post-Covid Era and Its Impact on Faculty Members’ Occupational Well-being and Teaching Self Efficacy: A Path Analysis Using the UTAUT 2 Model"	Online survey methodology and path analysis	350	Significant positive relationships between occupational well-being and teacher self-efficacy with UTAUT2 variables.
Yin M.; Han B.; Ryu S.; Hua M. [33], “Acceptance of Generative AI in the Creative Industry: Examining the Role of AI Anxiety in the UTAUT2 Model"	Structural equation modeling	326	UTAUT2 effort expectancy, price value and hedonic motivation positively influence the intention to use generative AI, while performance expectancy does not show a statistically significant effect.
García de Blanes Sebastián M.; Sarmiento Guede J.R.; Antonovica A. [34], “Application and extension of the UTAUT2 model for determining behavioral intention factors in use of the artificial intelligence virtual assistants"	Structural equation modeling	304	The factors of habit, trust and personal innovativeness have a significant impact on the adoption of AI virtual assistants.
Koh L.Y.; Yuen K.F. [35], “Public acceptance of autonomous vehicles: Examining the joint influence of perceived vehicle performance and intelligent in-vehicle interaction quality"	Structural equation modeling	500	The identified factors of UTAUT2 and Computer as Social Actor are significant in predicting the acceptance of autonomous vehicles.
Ghazi K.; Kattara H.; Salem I.E.; Shaaban M.N. [36], “Benefit-triggered or trust-guided? Investigation of customers’ perceptions toward AI-adopting hotels amid and post COVID-19 pandemic"	Structural equation modeling methodology	416	Perceived benefits of the technology mediate more than customer trust in behavioral intention toward hotels adopting AI during and after the COVID-19 pandemic.
Romero-Rodríguez J.-M.; Ramírez-Montoya M.-S.; Buenestado-Fernández M.; Lara-Lara F. [37], “Use of ChatGPT at University as a Tool for Complex Thinking: Students’ Perceived Usefulness"	Methodology of the model-based methodological approach UTAUT2	400	Experience, performance expectancy, hedonic motivation, price value and habit were influential in the behavioral intention to use ChatGPT.
Bervell B.B.; Kumar J.A.; Arkorful V.; Agyapong E.M.; Osman S. [38], “Remodeling the role of facilitating conditions for Google classroom acceptance: A revision of UTAUT2″	Methodology not specified	No sample specified	Facilitating Conditions partially mediate the effect of Performance Expectancy, Effort Expectancy, Social Influence and Hedonic Motivation on Behavioral Intention to use Google Classroom.
Almaiah M.A.; Alyoussef I.Y. [39], “Analysis of the effect of course design, course content support, course assessment and instructor characteristics on the actual use of e-learning system",	Methodology not specified	No sample specified	Results of the effect of course design, course content support, course evaluation and instructor characteristics on the actual use of an e-learning system.

many STEM areas, such as data analysis in science or automation in engineering, also contributes to its perceived relevance in these contexts.

Moreover, STEM faculties tend to have more robust technological infrastructure and greater resources to implement and experiment with AI technologies. This, combined with the growing labor market demand for professionals with AI skills, drives higher adoption in these educational fields.

There are multiple implications of these findings. First, they suggest the need for more balanced research exploring AI adoption in non-STEM disciplines to ensure inclusive implementation across higher education. Second, they indicate the importance of a holistic approach that considers not only technical aspects but also pedagogical, social, and economic factors in AI adoption.

Fig. 3 presents a VOSviewer bibliometric map that visually illustrates the collaboration and relevance of countries in the realm of academic research. Nodes and connections reflect the intensity of scientific activity and coauthorship relationships between nations. Countries such as India and China are shown as central nodes with numerous connections, suggesting a high production of research and possibly significant international collaborations. The distinct colors of the nodes may represent different regions or research groupings, while the lines connecting the countries indicate the frequency of collaboration between them. The concentration of connections among Middle Eastern countries such as Jordan, Turkey, and the United Arab Emirates suggests a regional collaboration network. In contrast, links extending to and from the United States and European countries such as Germany and the United Kingdom reflect a global influence and an extensive collaboration network in research. This analysis is useful for understanding global collaboration dynamics and the leadership or intermediary roles that certain countries have in the global research landscape.

Bibliometric map analysis also revealed a notable concentration of research on AI adoption in higher education in countries such as Malaysia and Indonesia. Several relevant factors can explain this phenomenon. First, these countries have implemented aggressive educational policies oriented toward integrating advanced technologies into their higher education systems [19]. Additionally, there has been significant governmental and private investment in educational technology infrastructure in these regions [10]. Another relevant factor is the existence of strong international collaborations between universities in these countries and leading global technological institutions [11].

This finding has important implications for future research and practice in the field. This suggests the need for comparative studies to understand how different national contexts influence AI adoption in higher education. Additionally, it highlights opportunities for international collaboration that can benefit from diverse experiences in AI implementation. Moreover, this study emphasizes the importance of considering cultural and economic factors when studying AI adoption in higher education settings.

This systematic review revealed significant differences in AI adoption between general higher education and engineering education. In the engineering field, there is a faster and more widespread adoption of AI [17], with greater integration of these technologies into curricula and research projects. Both students and faculty in engineering tend to be more familiar with AI concepts. In contrast, higher education generally exhibits a more varied adoption pattern. Some disciplines show resistance to AI incorporation [20], and the applications of these technologies are limited or less evident in certain areas. In this context, there is a greater need for contextualization and adaptation of AI tools for effective use. These differences highlight the necessity of developing tailored approaches for implementing AI in different academic disciplines. The prominence of STEM terms in the red cluster of the bibliometric map reinforces this observation, suggesting a bias toward technical disciplines in AI research in higher education. This bias can be explained by the natural affinity between STEM disciplines and AI, the greater availability of resources and technical expertise in these faculties, and a clearer perception of AI's applicability in technical fields.

3.1. Factors predicting the adoption of artificial intelligence among students, faculty and staff at higher education institutions

The perceived performance expectancy of AI technology, that is, the extent to which it is believed to enhance performance and productivity in educational tasks, is revealed to be a highly positive factor [37,40,41]. On the other hand, hedonic motivation, or the level of satisfaction and entertainment value associated with using AI tools, also strongly predicts adoption intentions among students and other groups according to various studies [37,40,42,43].

In the same context, certain specific groups present additional relevant predictors. For example, among university students, perceived ease of use and social influence also play significant roles [44,45]. Consequently, the main cross-cutting predictors are performance expectancy and hedonic motivation, while in certain populations, social influence and perceived ease of use are also determinants of AI acceptance in education.

It is important to address both the performance expectancy and hedonic motivation associated with AI use to promote greater acceptance and adoption by students and faculty. The importance of considering perceived ease of use and social influence, especially in the context of university students, underscores the need to adopt implementation strategies that focus not only on the technical capabilities of AI but also on its integration within the educational ecosystem in alignment with social norms and user expectations.

Moreover, the identification of specific predictors in different user groups suggests that adoption strategies should be adapted and personalized. For instance, while social influence and ease of use are critical factors for university students, other groups may have

Table 3
Main factors identified.

Factor UTAUT2	Conceptual definition	Key findings
Performance expectation	Refers to the degree to which an individual believes that using AI will improve their academic or job performance.	Several studies [37,46] found this to be a significant predictor of intention to use AI. Likewise, the UTAUT2 model highlights the importance of performance expectancy in influencing students' behavioral intention and use of AI applications in higher education [47–56].
Expectation of effort	Effort expectancy is defined as the degree of ease associated with using a technology. This construct refers to the individual's perception of how much mental and physical effort will be required to learn to use and operate a new technology or system.	[42] found that this factor is especially relevant for students with no previous AI experience. It is also a crucial factor affecting students' willingness to use AI in educational settings [47,50,52,53,56].
Social influence	Refers to the degree to which an individual perceives that other people important to him or her believe that he or she should use AI.	[44] identificaron este factor como crucial en culturas colectivistas. Así mismo, es evidente la influencia de los compañeros y de los factores sociales en la aceptación y el uso de la IA en la enseñanza superior, lo que subraya la importancia de la influencia social en el modelo UTAUT2 [47,50,52,54,56].
Enabling conditions	Extent to which an individual believes that there is an organisational and technical infrastructure to support the use of AI	[27] found that this factor has a direct effect on the actual use of AI. Furthermore, the presence of enabling conditions is shown to influence the intention and actual use of AI applications in higher education [47,51,53,56].
Hedonic motivation	Refers to the pleasure or enjoyment derived from the use of a technology.	[37,57] found that this factor is particularly relevant in AI applications such as ChatGPT. Furthermore [58], indicates that hedonic motivation influences behavioral intention in the acceptance of Academic Information Systems (AIS).
Perceived risk	This construct is defined as the individual's perception of uncertainty and adverse consequences potential associated with the use of a new technology.	Misunderstanding of AI Concept, Misuse of AI Resources, Mismatching of AI Pedagogy, Privacy Security Risk, Transparency Risk, Accountability Risk, Bias Risk, and Perceived Risk are identified as the key factors contributing to perceived risk in AI adoption in higher education [59]. In addition, perceived risk negatively influences ($B = -0.107$) the intention to use ChatGPT frequently [60].
Habit	It refers to the disposition in which people tend to perform behaviors automatically due to prior learning.	[32,61] found that habit is a strong predictor of continued AI use.
Perceived ethics	Perceived ethics refers to individuals' understanding and awareness of ethical issues related to artificial intelligence.	Exposure to ethics instruction and internship experiences significantly influences communication students' ethical perceptions and behavioral inclinations of adopting AI applications [62]. Moreover, the use of ChatGPT positively and significantly influences the perceived ethics of Generation Z students [63].

different motivations or barriers that need to be addressed. This personalization would not only increase technology acceptance among various groups but also maximize its positive impact on the educational process.

Therefore, the effective integration of AI technology in educational environments depends not only on the objective improvement it can offer in terms of performance and productivity but also on how these advancements are perceived and accepted by end-users.

3.2. Factors related to UTAUT2 theory influencing AI adoption in higher education

Table 3 presents the main factors influencing the adoption of AI in higher education.

3.3. Collaboration and innovation: trends in educational research with UTAUT2

The use of the UTAUT2 model in educational research to evaluate the adoption and use of new technologies in higher education, such as AI, offers a comprehensive and robust framework for understanding the factors driving or inhibiting AI adoption [2,15]. As previously explained, the model is based on several fundamental constructs, including Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, and Habit [4,6]. Together, these constructs provide a holistic view of how and why students and faculty might accept and utilize AI technologies in their teaching and learning processes.

Collaboration and innovation (see Figs. 2 and 3) reinforce the idea that there is an ongoing trend in educational research using the UTAUT2 theory. The relevance and frequency of fundamental terms such as “behavioral intent,” “acceptance,” and “e-learning” are evident in the literature focused on the UTAUT2 Model as applied to technology and education. The prominence of these terms demonstrates the dominant interest in understanding how behavioral intentions and technology acceptance drive adoption in educational settings. Furthermore, the interconnection between these concepts and other education-specific terms, such as “higher education” and “educational institutions”, reflects a concentration on researching the adoption and use of new technologies in higher education.

Regarding the structure of international collaboration in educational research related to AI, countries such as India and China stand out as key nodes in the scientific collaboration network. This indicates not only a high production of research but also the significance of international collaboration. Similarly, the notable concentration of connections among Middle Eastern countries contrasts with the extensive collaboration network linking the United States and European nations such as Germany and the United Kingdom. This reflects a global landscape of cooperation in research focused on measuring the impact and use of artificial intelligence with the UTAUT2 model. Consequently, there is convergence that highlights the importance of interdisciplinary studies and global collaboration in advancing the understanding and implementation of emerging technologies such as AI in educational contexts.

3.4. Analysis of moderators and mediators of AI adoption in higher education

The analysis revealed several moderating and mediating factors that influence the relationship between UTAUT2 constructs and the adoption of AI in university settings. These factors provide a more nuanced understanding of the adoption process, enabling the identification of more specific and effective interventions.

Regarding moderators, three main factors were identified. First, prior experience with technology was found to moderate the relationship between effort expectancy and usage intention [42]. found that this relationship was stronger for individuals with less technological experience. Second, age emerged as a significant moderator in the relationship between social influence and usage intention [32]. reported that this relationship was more pronounced in younger users. Finally, academic discipline also showed a moderating effect [37]. observed that the relationship between performance expectancy and usage intention was stronger in STEM fields.

Concerning mediators, three key factors were identified. Technological self-efficacy, according to Ref. [44], partially mediates the relationship between facilitating conditions and usage intention. Additionally [33], reported that AI anxiety acts as a mediator in the relationship between effort expectancy and usage intention. Finally [28], observed that perceived usefulness mediates the relationship between performance expectancy and usage intention.

These findings on moderators and mediators significantly enrich the understanding of the factors influencing AI adoption in higher education. By providing a more detailed and contextualized view of the adoption process, these results enable the design of more precise implementation strategies tailored to the specific characteristics of different groups within the university environment.

3.5. Subgroup analysis of AI uptake in higher education

Subgroup analysis of artificial intelligence (AI) adoption in university settings revealed significant differences in adoption patterns among various segments of the academic population. These findings highlight the importance of developing differentiated AI implementation strategies that consider the specific characteristics of each subgroup within the university community.

In the comparison between students and faculty, different predictors of usage intention were observed. For students [37], found that hedonic motivation and social influence were stronger predictors. In contrast [32], reported that, for faculty, performance expectancy and facilitating conditions had a greater influence.

Examining the differences between undergraduate and graduate students [42], reported that perceived ease of use was a more critical factor for undergraduate students. Conversely [46], observed that performance expectancy had a greater impact on graduate students.

Regarding academic disciplines, distinct patterns were found between STEM and non-STEM areas [17]. reported that in STEM disciplines, performance expectancy and technological self-efficacy were stronger predictors. In contrast [20], found that in non-STEM disciplines, social influence and facilitating conditions were more relevant.

Finally, differences between public and private institutions were identified [27]. found that, in public institutions, facilitating conditions and price value were more influential. Meanwhile [28], reported that, in private institutions, performance expectancy and hedonic motivation had greater impacts. Consequently, these findings underscore the need to adopt differentiated approaches to AI implementation in university settings, considering the specific characteristics of each subgroup to maximize the effectiveness of adoption strategies.

3.6. Theoretical implications

This study contributes to the validation and extension of unified theory of acceptance and use of technology 2 (UTAUT2) in the specific context of artificial intelligence (AI) adoption in university settings. The findings corroborate the versatility and robustness of the UTAUT2 model in elucidating the factors that influence the acceptance and effective use of emerging technologies such as AI in higher education.

This research supports the relevance of UTAUT2's core constructs, such as performance expectancy, hedonic motivation, perceived ease of use, and social influence, in predicting AI adoption intentions and behaviors among students, faculty, and administrative staff. Additionally, it identifies differences in the relative importance of certain predictors based on the specific user group.

Moreover, the study expands the existing knowledge by categorizing the most common perceptions and attitudes toward AI applications in higher education contexts. This highlights the positive influence of factors such as habit, performance expectancy, and hedonic motivation on the acceptance of these technologies.

From a theoretical perspective, these findings support the applicability of UTAUT2 in higher education and contribute to a deeper understanding of the determinants of AI adoption in this specific context. Furthermore, the results suggest the need to consider additional factors or extensions of the model to better capture the complexity of perceptions and behaviors of different user groups.

3.7. Practical implications

The findings of this study have significant practical implications for higher education institutions seeking to effectively integrate AI technologies into their educational and administrative practices.

First, by identifying the key factors influencing AI acceptance, this study provides valuable insights for developing effective implementation strategies. Institutions can design initiatives that highlight the perceived benefits and added value of AI while fostering a satisfying and motivating user experience.

Additionally, recognizing the differences in adoption predictors among students, faculty, and administrative staff allows institutions to tailor their approaches and resources to meet the specific needs and expectations of each group. For example, training programs for students can focus on perceived ease of use and social norms related to AI.

The study also underscores the importance of addressing existing barriers and concerns, such as distrust and lack of knowledge about AI. Institutions can design awareness and training programs to increase understanding and confidence in these emerging technologies. Insights into common perceptions and attitudes toward AI can guide the design and implementation of AI applications and tools that align with the needs and preferences of end-users. This alignment can enhance adoption and effective use, maximizing the positive impact of AI on teaching, learning, and university management processes.

It is recommended that institutional policies develop clear guidelines on the ethical and responsible use of AI in educational contexts, establish interdisciplinary committees to guide AI implementation, and create incentives for AI adoption across various disciplines. For implementation strategies, it is suggested that differentiated training programs be designed for students and faculty, AI tools be gradually implemented starting with pilot projects, and interdisciplinary collaboration for AI applications be promoted.

For faculty professional development, workshops and courses on AI applications in education, the creation of communities of practice to share experiences and best practices, and the integration of AI competencies into faculty development standards are proposed. In terms of ethical and privacy considerations, developing ethical guidelines for AI use in research and teaching, implementing robust data protection and privacy measures, and educating the university community about the ethical and social implications of AI are recommended.

This systematic review makes significant contributions to the discourse on AI in higher education. First, it offers a comprehensive and updated synthesis of the factors influencing AI adoption in this field, integrating findings from recent and diverse studies. It also highlights underresearched areas, such as AI adoption in non-STEM disciplines and diverse cultural contexts, opening new avenues for future research. This review proposes an extension of the UTAUT2 model specifically adapted to the context of AI in higher education, incorporating emerging factors such as ethics and privacy. Additionally, this study provides a cross-cultural analysis, offering insights into how AI adoption varies across different national and cultural contexts. Finally, this study has practical implications, providing evidence-based recommendations for the effective implementation of AI in higher education institutions.

4. Conclusions

This research has provided valuable insights into the factors influencing the acceptance of artificial intelligence (AI) in university contexts, using the UTAUT2 model as a theoretical framework. The findings reveal a complex interaction of factors that determine AI adoption in higher education, highlighting the need for a nuanced and contextualized approach to implementing these technologies.

A significant finding is the variation in adoption patterns among different groups and contexts. Performance expectancy and hedonic motivation emerged as consistent predictors of usage intention among students, faculty, and administrative staff. However, the relative importance of factors such as perceived ease of use and social influence varied by group, underscoring the need for differentiated implementation strategies.

This research also sheds light on the differences in AI adoption between STEM and non-STEM disciplines, as well as between public and private institutions. This suggests that AI integration in higher education cannot follow a one-size-fits-all approach but must be tailored to the specific characteristics of each discipline and institution.

A novel aspect of this study is the identification of moderating and mediating factors in AI adoption, such as prior technology experience and technological self-efficacy. These findings expand our understanding of the UTAUT2 model in the specific context of AI in higher education, providing a more solid foundation for future research and practical applications.

The persistence of barriers such as distrust and lack of knowledge about AI, despite generally positive perceptions, indicates the need for ongoing efforts in education and awareness. This is particularly relevant given the rapid evolution of AI technologies and their growing importance in various academic and professional fields.

From a methodological perspective, this study demonstrates the utility of combining bibliometric analysis with a systematic literature review to obtain a more comprehensive view of the field. The use of bibliometric maps allowed for visualizing research trends and international collaborations, providing valuable context for interpreting the findings of the systematic review.

However, it is important to acknowledge the limitations of this study. The cross-sectional nature of most of the analyzed research limits our ability to understand how adoption factors evolve over time. Additionally, the concentration of research in certain countries and disciplines suggests the need for a broader and more diverse exploration of the topic.

These limitations point to several directions for future research. Longitudinal studies are needed to examine how adoption factors change as users gain experience with AI technologies. Future research should also explore AI adoption in non-STEM disciplines and diverse cultural contexts more deeply to provide a more comprehensive and nuanced understanding of this phenomenon.

Furthermore, given the rapid evolution and increasing sophistication of AI, it will be crucial to examine how ethical factors and privacy concerns influence the adoption of these technologies in educational settings. This might involve extending the UTAUT2 model to incorporate constructs related to ethics and privacy.

Therefore, this study significantly contributes to our understanding of AI adoption in higher education, providing a solid foundation for future research and guiding the development of policies and practices in this rapidly evolving field. The findings underscore the need for a multifaceted and adaptive approach to AI implementation in educational contexts, considering the diverse needs and characteristics of different user groups and institutional environments.

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The data will be made available upon request.

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Benicio Gonzalo Acosta-Enriquez: Visualization, Resources, Formal analysis, Conceptualization. **Emma Verónica Ramos Farroñan:** Writing – review & editing, Methodology. **Luigi Italo Villena Zapata:** Writing – original draft, Conceptualization. **Francisco Segundo Mogollon Garcia:** Writing – review & editing, Methodology, Investigation. **Helen Catalina Rabanal-León:** Writing – original draft, Methodology, Investigation, Conceptualization. **Jahaira Eulalia Morales Angaspilco:** Writing – review & editing, Methodology. **Jesús Catherine Saldaña Bocanegra:** Moíses David Reyes Pérez, Visualization, Investigation.

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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