



RESEARCH ARTICLE

Measuring Artificial Intelligence Integration in Higher Education: A Bibliometric Analysis of Quantitative Studies

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ABSTRACT

This study explores the current state of Artificial Intelligence (AI) adoption in higher education, evaluating its scope via bibliometric methods. The research builds upon the knowledge acquired from quantitative studies and establishes guidance for future studies. A total of 24 publications from the combined database of Scopus and Web of Science (WOS) were collected and used as the resource for the bibliometric analysis. The bibliometric analysis using Biblioshiny identified seven indicators, including annual publications, the top 10 contributing countries, the most relevant sources, a thematic map, motor and niche themes, emerging or declining themes, and basic themes. In addition, for the keyword analysis, the authors used the VOSviewer, which identified three clusters: pedagogy, AI tools, and ethics. As a result, the paper provides an improved understanding of AI adoption in education and a framework that includes both students' and educators' perspectives on the measures and quantitative research in AI utilization in education. Such knowledge not only provides significant information on the current state of literature and trends but also implications for educators, administrators, and educational technology (EduTech) suppliers.

Keywords: AI Adoption, Education, Students, Educators, Bibliometric Analysis



DOI: 10.26650/JODA.1536942

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Submitted: 21.08.2024

Revision Requested: 30.09.2024

Last Revision Received: 15.11.2024

Accepted: 23.11.2024

Published Online: 24.01.2025

Citation: Çifçi, H., Şahin, M. A., Çifçi, İ., & Çetin, G. (2024). Measuring Artificial Intelligence Integration in Higher Education: A Bibliometric Analysis of Quantitative Studies. *Journal of Data Applications*, 3, 33-62. <https://doi.org/10.26650/JODA.1536942>



Introduction

Artificial intelligence (AI) promises a great potential to transform education, with the advancement of various tools, particularly in the higher education area (Huang & Rust, 2018), including ChatGPT, Canva, Education Copilot, Grammarly, and Quillbot (EDUCAUSE, 2019). However, research indicates that AI adoption in educational institutions remains tentative (McGrath et al., 2023; Perrault & Clark, 2024), despite its substantial potential to revolutionise higher education compared to other technological breakthroughs (Bates et al., 2020). AI can benefit education in various ways, for instance, by enhancing learning analytics systems (Cerratto Pargman & McGrath, 2019), providing accurate and expeditious results, eliminating bureaucracy through algorithmic systems (Burrows et al., 2015), and improving effectiveness and outcomes in education and research (Klutka et al., 2018).

Hence, some authors (e.g., Zawacki-Richter et al., 2019) highlight the importance of deepening the insight into AI's effectiveness in higher educational settings, making this phenomenon interesting to explore (McGrath et al., 2023). However, there is still no consensus on AI integration in higher education (Molenaar, 2022). Various challenges have been suggested, shaping both non-academic and academic discourse mainly through conceptual and qualitative approaches. These include AI illiteracy (Luckin et al., 2022; Laupichler et al., 2022), fear of job losses (Akata et al., 2019), resistance to change and tendency to avoid the risk (Bearman et al., 2023), risk of biases and prejudice within data and regarding learning analytics (Mittelstadt et al., 2016), and limited funding for alternatives to traditional teaching methods (Wheeler, 2019).

A large volume of prior work on AI in higher education has paid more attention to technological implications through systematic reviews (Bearman et al., 2023; Bond et al., 2024; Laupichler et al., 2022), and in some cases through qualitative approaches (AI-Mughairi & Bhaskar, 2024). This leaves room for future investigation to better understand and reveal the factors influencing AI adoption in higher education practises (Buckingham Shum et al., 2019). Although these papers provide useful insights and knowledge on the current state of AI in education, none, to the best of our knowledge, sufficiently address the adoption challenges in foundational research, which questions why AI has not yet become a revolutionary element in education (Dhawan & Batra, 2020). Consequently, based on this perspective, it is relevant to guide AI implementation by analysing quantitative research that provides measurements on the actual adoption of AI in education.

This research addresses the need for further research on the potential of AI in educational environments while underscoring the importance of a close and more nuanced examination of the adoption within the educational practise that pertains to AI learning through quantitative

measures and scales. As a strictly bibliometric study, this research, therefore, seeks to offer pertinent guidance by reviewing quantitative studies on the optimal integration of AI into learning environments, ensuring the effective transfer of knowledge from AI as a theoretical concept to its practical application in higher education. As such, this research contributes to the development of more sophisticated AI models for education and provides insights into possible avenues for further research.

Literature Review

The higher education domain is growing at an unprecedented pace and requires theoretical development to advance the existing knowledge of AI from the stakeholders' point of view (Bond et al., 2024; Crompton & Burke, 2023). Since AI applications may not always be compatible with teaching and learning processes and goals, it becomes pertinent to identify educational contexts that can integrate AI in a manner that makes it easy for educators, students, and other stakeholders in education to use it for their intended pedagogical purposes.

Based on these considerations, the AI application in education can be organised in terms of beneficiaries divided into (a) student-centric AI applications and (b) educator-centric AI applications (Baker et al., 2019). However, comparatively, scholars have paid limited or modest efforts in researching this phenomenon, although evidence has indicated that there is much discussion about it (Dhawan & Batra, 2020). When the use and incorporation of AI-enabled technologies in educational contexts are considered, they should not simply be seen as matching with technology or design ideas or otherwise meeting the integration requirements set out by the formal technological frameworks. However, educators' and students' needs should also be considered when these technologies are to be incorporated into educational programmes (Luckin et al., 2016). In this regard, the present research outlines a broad systematic review of quantitative research involving students' and educators' AI adoption to guide future studies and technologies. The paper first explores the quantitative literature involving students and then focuses on research on AI adoption by educators as participants.

For example, Bisdas et al. (2021) discussed the topic from the student perspective and evaluated the attitude of medical and dental students about AI integration in their education, finding that students have positive attitudes towards incorporating AI into their training. Abdelwahab et al. (2023) searched business students' perceptions about AI integration and revealed the importance of curriculum and educational facilities updates for students' integration due to a lack of adequate knowledge of the increasingly AI-integrated work environment. Yuk Chan and Tsi's (2023) study regarding the AI integration of teachers that teachers can integrate AI to enhance teaching without replacing them. Mohd Rahim et al.'s (2022) study revealed that perceived trust is an important predictor of students' adoption of AI.

Chan and Hu's (2023) study revealed the students' main concerns about using AI as accuracy, privacy, and ethics, as well as the potential influences on personal growth, career opportunities, and societal norms. Li (2023) observed that the perceived usefulness (PU) and perceived ease of use (PEU) of AI-based systems had positive impacts on attitudes, behavioural intentions, and practical applications among students.

In contrast, college students' sentiments towards AI-based systems had no substantial influence on their learning motives to reach goals or subjective standards. However, the study of Bilquise et al. (2024) demonstrated that PU, autonomy, and trust did not significantly influence the acceptance of an advising chatbot. Foroughi et al. (2023) identified that factors such as performance expectancy, effort expectancy, hedonic motivation, and perceived learning value exert a significant impact on individuals' intentions to adopt the generative AI ChatGPT. Alhumaid et al. (2023) found that perceived compatibility, trialability, the perceived advantage, and ease of doing influence students' AI adoptions. Strzelecki (2023) found that habit is the most significant predictor of students' behavioural intention to adopt AI. Delcker et al. (2024) study revealed that students' attitudes towards AI are influenced by the perceived benefits of AI technology. Salloum et al. (2024) also revealed that students' willingness to adopt AI chatbots is affected by perceived usefulness, ease of use, and flow experience. Dahri et al. (2024) showed that the increased use of AI tools enhanced student satisfaction and significantly influenced learning outcomes. However, students' engagement and personal innovativeness did not play a significant role in affecting AI tool adoption. Table 1 showcases the summary of these studies.

Despite the importance of educators in the integration of AI-based technologies (Çelik, 2023; Seufert et al., 2021; Wang et al., 2024), there is a shred of limited empirical evidence explaining how educators use AI technologies in the higher education context, highlighting a gap in research on exploring educators' viewpoints on AI-based instruction (Çelik, 2023). Table 2 illustrates a summary of some of the recent quantitative studies related to AI adoption in higher education from educators' perspectives by highlighting the variables, theories, models, and frameworks involved.

Even though some valuable individual studies might not fully capture all the factors influencing the integration of AI for academia; Chatterjee and Bhattacharjee (2020) identified the perspective of stakeholders (i.e., teachers, students, administrative staff) in adopting AI into higher education. Wang et al. (2021) examined teachers' intention to adopt AI tools in their classrooms in higher education settings through the Technology Acceptance Model (TAM) with four additional dimensions, including anxiety, self-efficacy, attitude towards AI, and behavioural intention. An et al. (2023) studied the behavioural intentions of English teachers regarding the use of AI for teaching. Zhang et al. (2023) identified the factors for determining pre-service teachers' intentions to use AI. Wang et al. (2023) conceptualised

teachers’ AI readiness through four components—cognition, ability, vision, and ethics—and also explored their interrelationships and implications on teachers’ professional practise. Çelik (2023) developed an intelligent Technological Pedagogical Content Knowledge (TPACK) framework by extending it to an ethical aspect. In the work of Shwede et al. (2024), the moderated model of the perceived relationship regarding the adoption of the AI system trust in data privacy and security, learning personally and professionally, stakeholders’ needs, and policy and regulations on educational sustainability were examined using the socio-technical systems theory.

Ning et al. (2024) developed a five-item AI-TPACK scale based on the assumption of the interactional and combined consequences of AI technology, pedagogy, and subject matter in educational contexts. Wang et al. (2024) analysed pre-service teachers’ perspectives to integrate AI usage and found that anxiety, social influence, and performance expectancy strongly predicted behavioural intention rather than effort expectancy and facilitating conditions. Lastly, Jain and Raghuram (2024) examined the TAM and TPACK models with an additional dimension of perceived trust towards the adoption of Gen-AI by Indian higher education institution members. Hence, a variety of research provides fruitful insights and knowledge into the existing literature on AI adoption in higher education, encompassing different theories, models, and contexts. It strengthens the current work’s rationale by addressing areas needing further exploration in understanding AI-based deployment in academia, with prominent studies shown in Table 2.

Table 1. *Summary of Recent Quantitative Studies on AI Adoption in Higher Education Based on Students’ Perspectives.*

Author/s	Database	Objective	Constructs Used	Model/Theory	Key Findings
Bisdas et al. (2021)	WoS and Scopus	Measuring attitudes towards AI integration during the education phases of medical and dental students.	Attitudes and feelings (8 items)	N/A	The research established that students possessed a basic concept and a favourable attitude regarding the integration of AI into their learning.
Abdelwahab et al. (2023)	WoS	Understanding business students’ perception of how higher education institutions prepare them for workplaces with AI integration.	Awareness (2 items) Teaching facilities (1 item) Programme/curricula (3 items) Teaching of AI skills (2 items)	The Quality Indicator Model	The findings indicate that students cannot integrate AI due to higher education institutions (HEIs) insufficient infrastructure and opportunities for AI.

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Author/s	Database	Objective	Constructs Used	Model/Theory	Key Findings
Chan and Hu (2023)	WoS and Scopus	Measuring the perceptions of university students on generative AI Technologies.	Knowledge of generative AI Technologies (6 items) Willingness to use (8 items) Concerns (4 items)	John Biggs’ 3P Model	The students recognised the opportunities in individual instructional facilitation, writing and idea generation instruments, and research and analysis instruments. However, there were certain doubts and questions associated with the topics referring to accuracy, privacy, ethical questions, and the impact on the individual’s or society’s development, job opportunities, perspectives, and norms.
Delcker et al. (2024)	WoS and Scopus	Exploring the perceptions and expectations of first-year students on AI tools integrating the DigiComp2.2 framework.	Skills (4 items) Knowledge (6 items) Attitudes (5 items)	The Unified Theory of Acceptance and Use of Technology (UTAUT) Model	This shows that first-year students’ attitudes towards AI are the main contributors to the intended use of AI tools. Furthermore, the perceived benefits of AI technology are antecedent variables for the perceived suitability of AI robots to substitute humans as cooperation partners.
Salloum et al. (2024)	Scopus	Measuring students’ perceptions of adopting AI across various educational institutions.	User satisfaction (3 items) PU (3 items) PEU (3 items) Flow Experience (2 items) Adoption of Chatbots (2 items)	The Technology Acceptance Model (TAM), Flow Theory	All predictors positively affected the students’ intention to adopt AI chatbots.

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Author/s	Database	Objective	Constructs Used	Model/Theory	Key Findings
Mohd Rahim et al. (2022)	WoS and Scopus	Identifying factors that influence the effectiveness of chatbot adoption in the HEI context.	Performance expectancy (5 items) Effort expectancy (5 items) Social influence (5 items) Facilitating conditions (5 items) Hedonic motivation (3 items) Habit (3 items) Interactivity (5 items) Design (5 items) Ethics (4 items) Perceived trust (4 items) Behavioural intention (3 items) Use intention (4 items)	UTAUT2, Information Systems (IS) Theory	Perceived trust was significantly impacted by interactivity, design, and ethics. Moreover, the results revealed that perceived trust, performance expectancy, and habit towards the use of chatbots had a significant impact on behavioural intention.

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Author/s	Database	Objective	Constructs Used	Model/Theory	Key Findings
Dahri et al. (2024)	WoS and Scopus	Measuring students’ intention to adopt AI tools in higher education institutions.	Performance Expectancy (5 items) Facilitating Conditions (5 items) Students’ Engagement (4 items) Assessment Effectiveness (4 items) Students’ Interaction (5 items) Information Accuracy (5 items) Personal Innovations (6 items) Pedagogical Fit (5 items) AI Tools Use (4 items) Behavioural Intentions (3 items) Student Satisfaction (4 items) Improve students’ Academic Performance (4 items)	UTAUT	Performance and effort expectancy, AI tool information accuracy, pedagogical fit, and student interaction played a significant role in the acceptability and usage of AI tools in higher education qualifications.
Foroughi et al. (2023)	WoS and Scopus	Investigating the determinants of the intention to use ChatGPT for educational purposes.	Performance Expectancy (6 items) Effort Expectancy (4 items) Social Influence (3 items) Facilitating Conditions (4 items) Hedonic Motivation (3 items) Learning Value (4 items) Habit (3 items) Personal Innovativeness (3 items) Information Accuracy (3 items) Intention to Use (3 items)	UTAUT2	Performance and effort expectancy, hedonic motivation, and learning value influenced the willingness to use ChatGPT, while personal innovativeness and information accuracy negatively moderated the relationships between ChatGPT use and its determinants.

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Author/s	Database	Objective	Constructs Used	Model/Theory	Key Findings
Alhumaid et al. (2023)	Scopus	Measuring students' perceptions of using AI for educational purposes in the UAE.	Artificial Intelligence Application Adoption (2 items) Perceived Compatibility (3 items) Triability (3 items) The relative advantage Ease of Doing Business (3 items) Technology Export (3 items)	Diffusion Theory	The results show that the diffusion theory variables have a greater impact compared to the ease of doing business and technology export variables.
Strzelecki (2023)	WoS and Scopus	Developing a model examining the predictors influencing the adoption and use of ChatGPT among students in higher education.	Performance expectancy (4 items) Effort expectancy (4 items) Social influence (3 items) Facilitating conditions (4 items) Hedonic motivation (3 items) Habit (4 items) Behavioural Intention (3 items) Personal innovativeness (4 items) Use Behaviour (1 item)	UTAUT2 (Extended UTAUT Model)	Habit emerged as the best predictor of behavioural intention, with performance expectancy and hedonic motivation following as the most significant predictors. Behavioural intention, followed by personal innovativeness, stood out as the most dominant determinant of use behaviour.

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Author/s	Database	Objective	Constructs Used	Model/Theory	Key Findings
Li (2023)	WoS and Scopus	Investigating the factors influencing the college students' engagement with AI-based systems and examining the role of learning motivations.	PEU (5 items) PU (5 items) Attitude (4 items) Learning motivation- Learning interest (5 items) Learning motivation- Achieving goal (4 items) Learning motivation- Subjective norm (6 items) Behavioural intention (4 items) Actual use (4 items)	TAM	PU and the perceived ease of use of AI-based systems had positive effects on students' attitudes, behavioural intentions, and engagement with AI-based systems. However, college students' attitudes towards AI-based systems had no significant influence on their learning motivation related to the achievement of their goals and subjective norms.
Bilquise et al. (2024)	WoS and Scopus	Identifying antecedents of behavioural intention in university students' use of an academic advising chatbot.	PEU (4 items) PU (4 items) Perceived Autonomy (5 items) Perceived Trust (5 items) Anthropomorphism (5 items) Social Influence (4 items) Behavioural Intention to Adopt (3 items)	TAM, UTAUT, The Service Robot Acceptance (sRAM) Model, The Self-Determination Theory (SDT) Model	The analysis of the results obtained shows the influence of functional elements, PEU, and social influence on the behavioural intention to accept the chatbots.

Table 2. Summary of Recent Quantitative Studies on AI Adoption in Higher Education Based on Educators' Perspectives

Author/s	Database	Objective	Constructs Used	Model/Theory	Key Findings
Wang et al. (2021)	WoS and Scopus	Measuring teachers' intention to adopt AI tools in their classes in higher education settings.	Anxiety (4 items) Self-efficacy (2 items) Attitude towards AI (2 items) PEU (2 items) PU (3 items) Behavioural Intention (4 items)	TAM	Perceived predisposing factors with respect to the adoption of AI-based applications by the teachers included attitudes towards use (ATU), PEU, PU, subjective norms (SE), and actual use (AN). SE had a positive impact on both PEU and ATU, which paved the way for adopting AI. In addition, strengthening SE diminished teachers' resistance (AN) towards adopting AI in teaching.
Yang et al. (2021)	WoS and Scopus	Examining the acceptance of the e-Schoolbag technology by K-12 teachers. The main objective of this study is to determine how teachers' Technological Pedagogical Content Knowledge (TPACK) abilities influence their inclination to use the e-Schoolbag.	Technological knowledge (TK) (3 items) Pedagogical knowledge (PK) (3 items) Content knowledge (CK) (3 items) Pedagogical content knowledge (PCK) (3 items) Technological content knowledge (TCK) (3 items) Technological pedagogy knowledge (TPK) (3 items) Technological pedagogical content knowledge (TPACK) (3 items) PU (6 items) PEU (6 items)	TAM, The Technological Pedagogical and Content Knowledge (TPACK) Model	TPACK significantly enhanced EOU and positively impacted the PU of e-Schoolbag applications, although its impact on PU scored comparatively lower. TK, PK, and CK did not have a direct effect on TPACK, while TPK and TCK directly contributed to TPACK. TK contributed significantly to both TPK and TCK, whereas PK affected TPK and PCK. CK notably influenced PCK.

Table 2. Summary of Recent Quantitative Studies on AI Adoption in Higher Education Based on Educators' Perspectives

Author/s	Database	Objective	Constructs Used	Model/Theory	Key Findings
Wang et al. (2023)	WoS and Scopus	Exploring AI readiness in four dimensions.	Cognition (5 items) Ability (6 items) Vision (3 items) Ethics (4 items)	N/A	It established a connection between teachers' ability in the application of AI and ethicality in education. Technical proficiency, visionary thinking, and ethical awareness were associated with higher levels of AI adoption by teachers. Fear of AI hampered educational innovation, while its adoption enhanced teachers' job satisfaction. The teacher cluster based on AI readiness implied that the level of innovation as well as the level of job satisfaction tended to be high, and this aspect was not affected by the socio-economic status and gender of the teacher.
Shwedeh et al. (2024)	Scopus	Analysing how the effects of AI adoption, trust (measured with data privacy and security), stakeholders' needs, policy, and regulations act as moderators in the perceived relationship for education sustainability.	Educational sustainability (7 items) Trust (8 items) AI adoption (9 items) Policies and regulations (7 items)	Socio-Technical Systems Theory	AI adoption positively affected educational sustainability. Policies and regulations did not affect educational sustainability. Trust positively affected educational sustainability. While policies and regulations moderated AI adoption and educational sustainability, they did not moderate AI adoption and trust.

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Author/s	Database	Objective	Constructs Used	Model/Theory	Key Findings
Chatterjee and Bhattacharjee (2020)	WoS and Scopus	Exploring how the stakeholders (i.e., teachers, students, administrative staff) adopt AI in higher education settings.	Perceived Risk (4 items) Performance Expectancy (5 items) Effort Expectancy (5 items) Facilitating Conditions (5 items) Attitude (5 items) Behavioural Intention (5 items) Adoption of AI in Higher Education (4 items)	UTAUT	By employing the UTAUT model, the research developed and empirically tested hypotheses to demonstrate the applicability of the model to encourage the use of AI among the stakeholders. Therefore, it suggested that the use of AI in the Indian higher education sector can enhance the governance and decision-making processes.
An et al. (2023)	WoS and Scopus	Exploring the integration of AI to enhance English as a Foreign Language (EFL) teachers' practises by investigating their perceptions, knowledge, and behavioural intentions in a K-12 setting.	Performance Expectancy (4 items) Effort Expectancy (4 items) Facilitating Conditions (4 items) Social Influence (3 items) AIL-TK (3 items) AI-TPK (7 items) AI-TPACK (10 items) Behavioural Intention (4 items)	UTAUT, TPACK	While performance expectancy, social influence, AI language technological knowledge, and AI-TPACK had significant positive predictive power on behavioural intention; effort expectancy, facilitating conditions, and AI-based pedagogical knowledge showed indirect effects on it.

Table 2. Summary of Recent Quantitative Studies on AI Adoption in Higher Education Based on Educators’ Perspectives

Author/s	Database	Objective	Constructs Used	Model/Theory	Key Findings
Zhang et al. (2023)	WoS and Scopus	Identifying factors influencing pre-service teachers’ behavioural intentions to use AI-based educational applications. It also explores gender differences in the proposed model.	PU (3 items) PEU (4 items) AI self-efficiency (4 items) AI Anxiety (3 items) Perceived enjoyment (3 items) Subjective norms (2 items) Job relevance (3 items) Behavioural intention (2 items)	TAM3	The research revealed that the determinants influencing behavioural intention were based on the TAM3 model in using AI-driven educational applications and highlighted the importance of addressing gender-specific elements in teacher education.
Çelik (2023)	WoS and Scopus	Developing a scale to measure the knowledge of teachers for using AI tools in instructional settings and extending TPACK components to include ethical considerations.	Intelligent–TPACK Scale (5 dimensions with 27 items)	TPACK	It proposed an Intelligent-TPACK framework with an improved scale.
Sun et al. (2024)	WoS and Scopus	Exploring teachers’ intention to integrate AI-based Teaching methods based on STEM educators.	TPACK (4 items) PU (4 items) PEU (4 items) Self-efficacy (4 items) Willingness to integrate AI (4 items)	TAM TPACK	A direct influence on WIAI was directed by TPACK, PU, PE, and SE. In addition, TPACK had a direct effect on PE, PU, and SE, while PE and PU influenced SE directly. The mediating roles of PE, PU, and SE were discovered in the relationship between TPACK and the willingness to integrate AI (WIAI).

Table 2. Summary of Recent Quantitative Studies on AI Adoption in Higher Education Based on Educators' Perspectives

Author/s	Database	Objective	Constructs Used	Model/Theory	Key Findings
Ning et al. (2024)	WoS and Scopus	Developing and validating an AI-TPACK measurement tool for teachers and exploring the interrelationships among its components to ensure alignment with theoretical assumptions.	AI-TK (5 items) AI-TCK (6 items) AI-TPK (6 items) AI-TPACK (5 items)	AI-TPACK	The developed framework functions as a comprehensive guide for the extensive evaluation of teachers' AI-TPACK, and a sophisticated grasp of how different AI-TPACK components interact leads to a more profound explanation of the generative mechanisms that underpin teachers' AI-TPACK.
Wang et al. (2024)	WoS and Scopus	Analysing pre-service teachers' perspectives regarding the adoption of generative AI into their Teaching practises.	Performance expectancy (4 items) Effort expectancy (4 items) Social influence (3 items) Facilitating conditions (4 items) GenAI Anxiety (4 items) Technology Self-Efficiency (4 items) GenAI TPACK (4 items)	UTAUT, TPACK	Generative Artificial Intelligence (GenAI) anxiety, social influence, and performance expectancy strongly predicted teachers' behavioural intentions. Effort expectancy and facilitating conditions have no impact on influencing their intentions.
Jain and Raghuram (2024)	WoS and Scopus	Examining the relationships among TAM, TPACK, and trust as predictors and their combined impact on the adoption of Gen-AI among undergraduate and postgraduate students and faculty members.	PEU (3 items) PU (3 items) TPACK (3 items) Trust (3 items)	TAM, TPACK	The study revealed that the relationships between age, gender, and the intention to adopt AI in higher education settings were non-compensatory and nonlinear.

Methodology

The search was conducted using the databases of the Web of Science (WoS) and Scopus, designed to locate articles related to the acceptance and integration of AI in higher education. The search string used for WoS is as follows: (“ARTIFICIAL INTELLIGENCE” OR “AI” OR “GENERATIVE AI” OR “GENERATIVE ARTIFICIAL INTELLIGENCE” (Topic) and “EDUCATION*” OR “HIGHER EDUCATION*” (Topic) and “TECHNOLOGY ACCEPTANCE” OR “ACCEPT*” OR “INTEGRATED*” OR “ADOPT*” OR “PERCEP*” OR “TOOL*” OR “CHATGPT*” OR “CHATBOT*” OR “TAM*” OR “UTAUT*” OR “*TPACK*” (Topic) and “STUDENT*” OR “TEACHER*” (Topic) and “QUESTIONNAIRE*” OR “SURVEY*” (Topic). The search string used for Scopus is as follows: (TITLE-ABS-KEY (“artificial intelligence” OR “ai” OR “generative ai” OR “generative artificial intelligence”) AND TITLE-ABS-KEY (“education*” OR “higher education*”) AND TITLE-ABS-KEY (“technology acceptance” OR “accept*” OR “integrate*” OR “adopt*” OR “percept*” OR “tool*” OR “ChatGPT*” OR “chatbot*” OR “tam*” OR “utaut*” OR “*tpack*”) AND TITLE-ABS-KEY (“student*” OR “teacher*”) AND TITLE-ABS-KEY (“questionnaire*” OR “survey*”) AND LANGUAGE (English)) AND PUBYEAR > 2019 AND (LIMIT-TO (DOCTYPE , “ch”) OR LIMIT-TO (DOCTYPE , “ar”)).

The generally preferred approach for bibliometric analysis is to use databases from either WoS or Scopus or to analyse each database separately due to the challenges linked with the integration process (Echchakoui, 2020). However, in this study, a procedure that merges data from the WoS and Scopus databases was adopted to provide a more comprehensive analysis. Figure 1 illustrates the research process flowchart following the PRISMA 2020 guidelines introduced by Page et al. (2021), which were adopted from the health and medical sciences into the field of tourism (Husamoglu et al., 2024). On July 05, 2024, a bibliometric analysis was conducted using data obtained from predefined databases (See Figure 1).

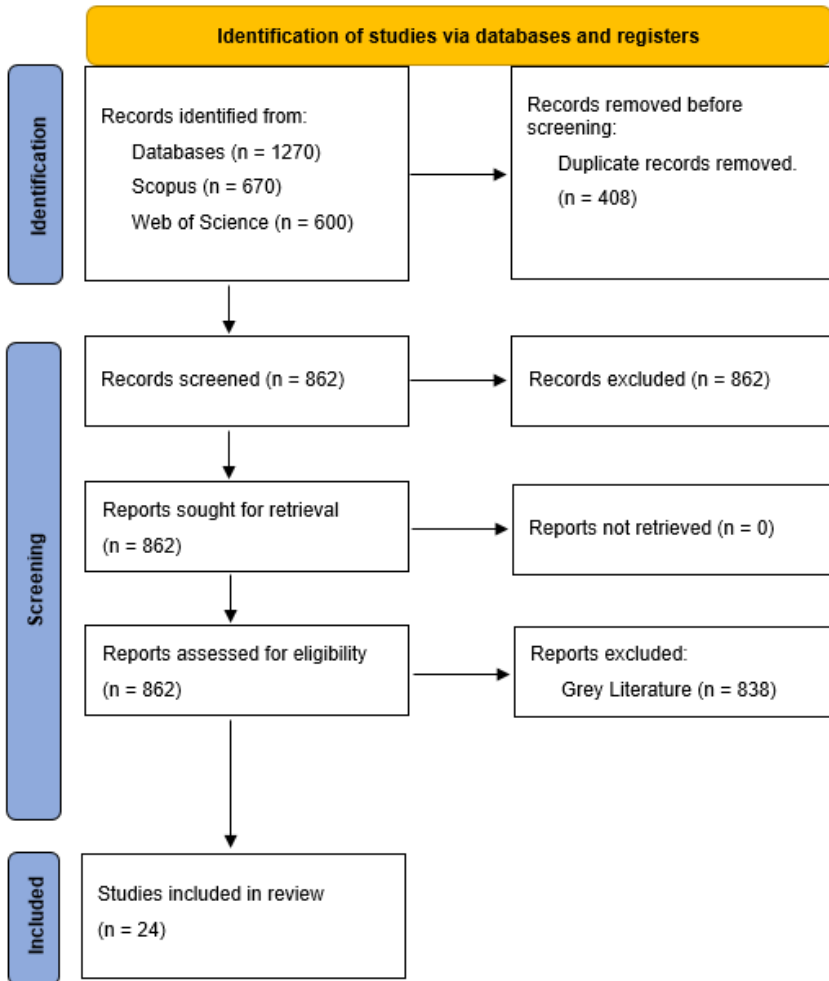


Figure 1. PRISMA 2020 flowchart.

A combined 24 publications, 21 from WoS and 24 from Scopus, were identified in this study. The bibliometric analysis does not consider the grey literature. The combined data includes two book chapters and 22 articles published since 2020. Productive authors, journals, countries, the most cited studies, annual publications, and thematic maps were analysed using the biblioshiny package in RStudio (2024.04.2+764), and the keyword analysis of the authors used the VOSviewer (1.6.20) software.

Table 3. Key information on the combined data.

Category	Details
DATA OVERVIEW	
Period	2020:2024
Source Types (Journals, Books, etc.)	13
Total Publications	24
Annual Growth Rate %	73,21
Average Document Age	1,04
Average citations per doc	26,04
CONTENT DETAILS	
Author's Keywords (DE)	100
AUTHORS	
Total Authors	123
Single-Authored Documents	3
AUTHORS COLLABORATION	
Single-Authored Documents	3
Average Co-Authors per Document	5,29
International Co-Authorships (%)	25
DOCUMENT TYPES	
Articles	17
Early Access Articles	5
Book Chapter	2

Table 3 shows a detailed summary of the main findings from the publications. The dataset, spanning from 2020 to 2024, comprises 24 documents sourced from 13 different journals and books, with an impressive annual growth rate of 73.21%. Due to the relatively novel nature of AI integration studies in quantitative research, which commenced in 2020, the research universe for this study encompasses works published from 2020 to the present year, 2024, during which the VOSviewer analysis has identified a total of 24 publications based on the specified search criteria. Consequently, the research universe for this study encompasses works published from 2020 to this year, 2024. The average age of the documents is 1.04 years, and each document has garnered an average of 26.04 citations (Sjöstedt et al., 2015, p. 6). In terms of content, the documents feature 100 distinct author keywords. The research involved 123 authors, with only three producing single-authored works. Collaboration is evident, with an average of 5.29 co-authors per document and 25% of the publications involving international co-authorship. The types of documents included 17 articles, five early-access articles, and two book chapters, highlighting a diverse range of scholarly outputs.

Results

Annual Publications

Between 2020 and July 6, 2024, 24 publications were produced. This includes 1 publication in 2020, 3 in 2021, 1 in 2022, and 10 in 2023. As of July 6, 2024, 9 publications have been recorded.

Top 10 Contributing Countries

Bibliometric analysis identified the top contributing countries to quantitative scientific research on AI integration in education based on country scientific production through the corresponding author's affiliation, aligning frequencies with the total article count. Therefore, in bibliometric analysis, the total frequencies of Country Scientific Production may be greater than the total documentation because each author is counted for each affiliation in an article, even if there are co-authors from other countries. On the other hand, the "Corresponding Author's Country" that assigns each article to a single country according to the affiliation of the corresponding author shows comparatively higher frequencies that are closer to the total unique word count. It also determines the Multiple Country Publications (MCP) index to estimate international cooperation through the identification of the articles having authors from different countries.

According to our findings, China led with the highest number of publications (39), demonstrating its intensive focus on advancing research and development. The United Kingdom followed with 10 publications, Malaysia ranked third with 9, Germany contributed 5, India had 4, and Pakistan contributed 3 publications. Several countries, including Australia, Finland, Jordan, Libya, the Netherlands, Poland, Singapore, Switzerland, and the United Arab Emirates, each produced 2 publications, indicating active participation in global scientific endeavours. Lastly, Ecuador, Egypt, Indonesia, Lithuania, Romania, Russia, Saudi Arabia, and Sweden each contributed 1 publication, reflecting a diverse geographic representation in scientific research (Please see Figure 2). The colour in Figure 2 represents the density of publications within specific geographical regions. This analysis underscores the collaborative and international nature of contemporary scientific endeavours, with substantial contributions from countries across various continents, highlighting a widespread commitment to advancing knowledge and addressing global challenges through scientific research.

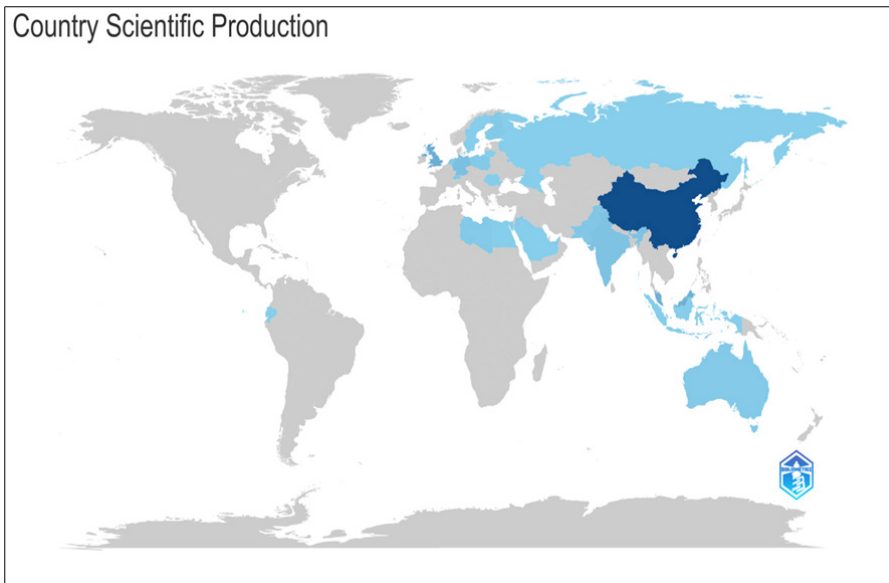


Figure 2. *Top 10 countries.*

Most Relevant Sources

The analysis of the most relevant sources in the dataset highlights the key journals and publications contributing to the research field (Figure 3). The journal “Education and Information Technologies” leads with the highest number of articles, totalling 5 publications. Following this, the “International Journal of Educational Technology in Higher Education” and “Sustainability” each have 3 articles, reflecting their significant roles in disseminating research. Journals such as “Computers in Human Behaviour,” “Interactive Learning Environments,” and “Studies in Big Data” each contributed 2 articles, showcasing their relevance in the field. Other notable sources with single contributions include “Behavioural Sciences,” “British Journal of Educational Technology,” “Educational Technology & Society,” “Frontiers in Public Health,” “Industry and Higher Education,” “International Journal of Data and Network Science,” and “International Journal of Human-Computer Interaction.”

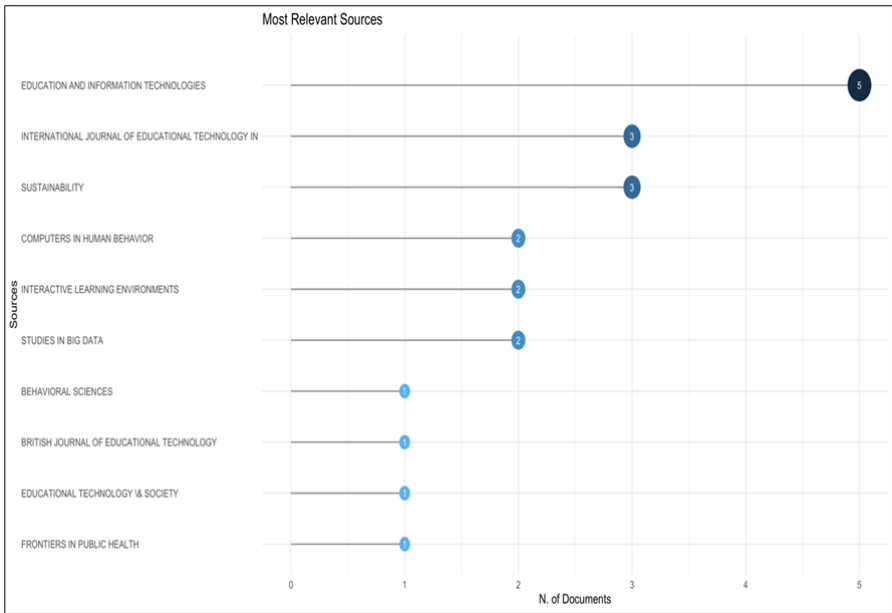


Figure 3. *The most productive sources.*

Thematic Map

The thematic map visualises specific keywords according to their centrality and density, thereby illustrating trends and focal points within the research domain. Figure 4 presents a thematic map with circles representing separate quadrants that outline clustered nodes (Aria & Cuccurullo, 2022; Callon et al., 1991; Cobo et al., 2011; Husamoglu et al., 2024). Configured to set the cluster frequency at eight, the Walktrap clustering algorithm provided a clearer understanding. The map, which uses the Walktrap clustering algorithm, evaluates the graph's structure and identifies clusters of documents characterised by high interaction status (Pons & Latapy, 2005).

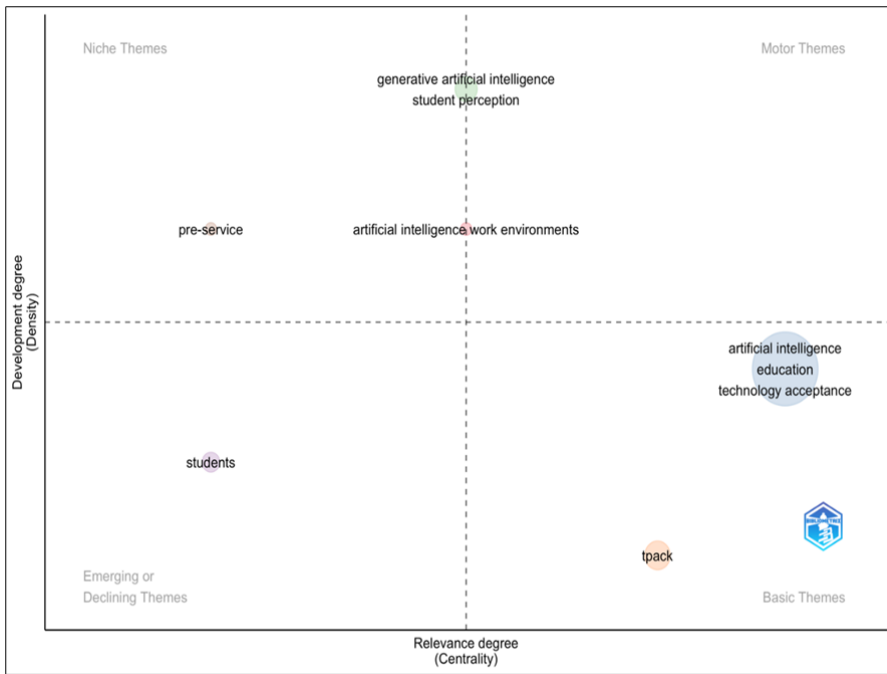


Figure 4. Thematic map.

Motor and Niche Themes

The upper right quadrant displays the related motor themes, which exhibit high density, centrality, and development (Aria & Cuccurullo, 2022; Cobo et al., 2011; Husamoglu et al., 2024). The motor themes identified in the thematic map consist of “generative artificial intelligence” and “student perception”. The high centrality of these themes indicates that they have strong connections with other research topics and occupy a central position within the research network. The high density indicates that these themes are actively being researched and are heavily discussed in the relevant literature. The “generative artificial intelligence” theme has become a central part of studies examining the creative and generative aspects of AI technologies. This theme shows that AI plays a significant role not only in data analysis and decision-making processes but also in creating new content, supporting creative processes, and driving innovation. The “student perception” theme encompasses studies investigating the effects of educational technologies and pedagogical practises on student perceptions. This theme is crucial for understanding the impact of AI and technological innovations in education on student experiences and learning outcomes.

Niche Themes

Niche themes with high density but low centrality are placed in this quadrant, emphasising their significance in the research field (Aria & Cuccurullo, 2022; Cobo et al., 2011; Husamoglu et al., 2024). “Pre-service” was identified as a niche theme in the thematic map. The high density of this theme indicates that it is actively researched and discussed extensively within its specific area. However, its low centrality means that it has limited interaction with other research topics and is relatively isolated within the research network.

Emerging or Declining Themes

Themes marked by low viscosity and weak centrality are considered either emerging or declining (Aria & Cuccurullo, 2022; Cobo et al., 2011; Husamoglu et al., 2024). The “Students” theme typically involves studies focused on various aspects of student life, experiences, and outcomes in higher educational settings. This could include research on student engagement, learning processes, academic achievement, and social interactions within educational institutions. As an emerging theme, “students” might represent a new area of interest that is beginning to gain attention and could see increased research activity in the future. This could be driven by new educational policies, technological advancements, or societal changes that highlight the importance of understanding student-related issues. Conversely, as a declining theme, “students” might indicate an area where research interest has saturated, possibly due to the maturation of the field, shifts in research priorities, or the resolution of key issues that previously drove research in this area.

Basic Themes

The quadrant showcases basic themes that, despite their low density, have high centrality and are crucial components in the research field (Aria & Cuccurullo, 2022; Cobo et al., 2011; Husamoglu et al., 2024). The identified basic themes in the thematic map are “artificial intelligence,” “education,” and “technology acceptance.” The high centrality of these themes indicates that they are foundational topics that interact with a broad range of other research areas. Their low density suggests that, while they are not the focus of intense, concentrated research activity at present, they remain crucial to the structure and coherence of the research network. This theme encompasses a broad range of studies related to the development and application of AI technologies. As a basic theme, AI serves as a critical underpinning for numerous research areas, including machine learning, data science, and robotics. Its foundational nature ensures that it remains highly relevant across diverse research topics, even if individual studies may not focus on AI alone. The theme of education covers various aspects of teaching, learning, curriculum development, and educational policy. As a basic theme, education is integral to a wide array of research endeavours, influencing studies in fields

such as psychology, sociology, and technology. Its central role highlights its importance in shaping research discussions and frameworks across multiple disciplines. This theme explores how individuals and organisations adopt and integrate new technologies. It includes theories and models that explain the factors influencing technology adoption, such as perceived ease of use and usefulness. As a basic theme, technology acceptance is pivotal for understanding the broader implications of technological innovations across different sectors, including healthcare, business, and education.

VOSviewer

VOSviewer visualisation provides an in-depth analysis of the key themes and relationships in AI research within education. The provided visualisation is a VOSviewer map highlighting the interrelationships between various concepts in the field of artificial intelligence and education. The map is divided into three distinct clusters, each representing different thematic connections (Please see Figure 5).

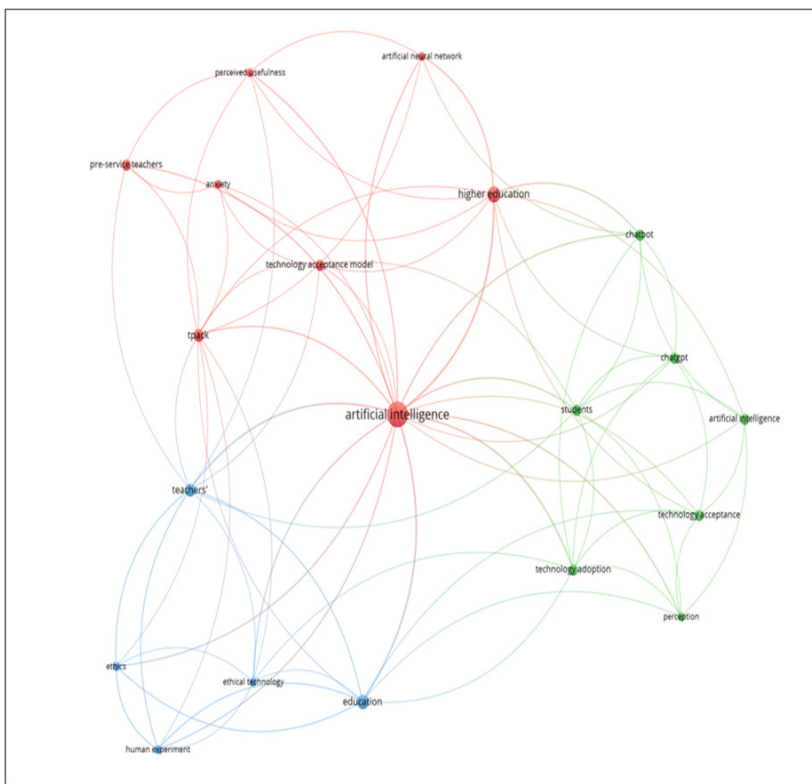


Figure 5. Authors' keywords cluster analysis.

Pedagogy: The red cluster centres around “Artificial Intelligence” and includes key terms such as “Anxiety,” “Artificial Neural Network,” “Higher Education,” “Perceived Usefulness,” “Pre-Service Teachers,” “TAM” and “TPACK.” This cluster indicates a focus on the integration of AI within educational settings, particularly in higher education. This study explores how AI and related technologies, such as neural networks, are perceived and adopted by pre-service teachers. The cluster also addresses the psychological aspects, such as anxiety, that might affect the acceptance and usefulness of these technologies. The TPACK framework is highlighted, emphasising pedagogical implications and the need for teachers to integrate technology effectively into their teaching practises.

AI tools: The green cluster also centres around “Artificial Intelligence” but focuses more on specific AI applications such as “Chatbot” and “ChatGPT.” It includes terms such as “Perception,” “Students,” “Technology Acceptance,” and “Technology Adoption.” This cluster illustrates the growing interest in using AI-driven chatbots in educational contexts. This study explores how students perceive these technologies and the factors influencing their acceptance and adoption. The cluster shows a strong emphasis on understanding how these AI tools can enhance the learning experience and the general receptiveness of students towards these innovations.

Ethics: The blue cluster shifts the focus to broader educational and ethical concerns with terms like “Education,” “Ethical Technology,” “Ethics,” “Human Experiment,” and “Teachers.” This cluster underscores the need to address the ethical aspects of implementing AI in education. It suggests a focus on ensuring that AI technologies are used responsibly and ethically, considering the potential implications for human experiments and the broader educational environment. The inclusion of “Teachers” emphasises the role of educators in navigating these ethical challenges and incorporating ethical technology into their teaching.

Overall, the VOSviewer map provides a comprehensive overview of the interconnections between AI and education. It highlights the importance of understanding the psychological, perceptual, and ethical dimensions of AI integration in educational settings. The map showcases a multifaceted approach to AI in education, emphasising the need for effective technology adoption, ethical considerations, and addressing the perceptions and anxieties of both teachers and students.

Conclusion

Theoretical Contribution

This research provides a theoretical background in offering a bibliometric analysis of the current state of the adoption of AI in higher education. It has set a path for understanding the

shift in the discourse about AI in higher educational settings by highlighting the publication trends, top contributing countries, thematic clusters, and keywords with bibliometric analysis methods like Biblioshiny and VOSviewer.

The conducted analysis indicates a noticeable and continuing pattern of growth in AI integration research in higher education, particularly from 2020 to 2024. This trend reflects an increased interest in the topic within academia, with contributions distributed across various countries and prominent journals, demonstrating a growing focus on the in-depth exploration of AI's applications and implications in educational contexts.

The thematic map identifies “Generative AI” and “student perception” as motor themes, indicating active research and significant connections with other topics, while “Artificial intelligence,” “education,” and “technology acceptance” function as basic themes that serve as foundational elements across the research landscape. Additionally, the “students” theme, which explores various aspects of student life in higher education, is emerging, reflecting growing interest, whereas “pre-service” education appears as a niche theme with a specialised focus but limited broader interaction.

The thematic clusters further reveal the focus areas within AI integration in education. The “pedagogy” cluster centres on incorporating AI into educational practises, addressing challenges like anxiety, and adopting frameworks such as TAM and TPACK. The “AI tools” cluster emphasises practical applications, such as chatbots and ChatGPT, examining how students perceive these technologies and the factors influencing their acceptance. Lastly, the “ethics” cluster highlights the need for responsible AI use, focusing on ethical considerations and the role of educators in navigating these challenges.

The thematic map and the identification of the core and emerging themes (e.g., pedagogy, AI tools, and ethics) provide a clear understanding of the key areas of interest and reveal the directions for the future growth of the theory. Altogether, the research highlights the role of AI in higher education institutions while presenting a systematic method for analysing its diffusion based on bibliometrics. The paper also provides and compares various alternative scales to measure AI integration in education from both students' and instructors' perspectives. Therefore, it provides a foundation for rational decision-making and establishes a direction for subsequent studies that will seek to optimise the positive effects of AI and minimise the challenges of AI integration learning environments.

Practical Contribution

This research provides recommendations that would be beneficial to policymakers, educators, education technology suppliers, and other stakeholders in higher education

institutions. As the list of topics might give an insight into, it offers a well-defined guideline for decision-making and strategizing by identifying the major themes and issues underlying AI implementation, including learning theories, technologies, and issues of ethics. Such knowledge can also help to design relevant interventions, standards, and actions to improve the integration of AI into teaching-learning processes.

Our analysis of emerging theme signals that educators and students might have concerns when using AI tools primarily because of the perceived lack of defined ethical rules. To address this issue, the development of a comprehensive guideline within educational settings becomes an urgent priority. This guideline should result from a collaborative effort involving relevant stakeholders, covering key topics, eliminating uncertainties regarding ethical issues, and achieving broad acceptance and applicability among its beneficiaries.

As discussed by Bisdas et al. (2021), students already have a positive attitude towards the use of AI tools in their education. However, some studies (e.g., Abdelwahab et al., 2023) posit that students face adoption challenges because the use of AI does not integrate into their curriculum and thereby have concerns about using AI tools just because of unknown standards of ethics (Mohd Rahim et al., 2022; Chan & Hu, 2023). Therefore, it would be wise for responsible authorities to organise training sessions specifically on how to properly employ AI tools. Through this strategy, educators can learn the pedagogical skills necessary to train AI applications for education and research purposes through “train the trainer” programmes and then also provide assistance to their students in gaining the knowledge needed to effectively use AI tools in education and research.

Limitations and Future Studies

This research has several limitations. First, the focus was mainly on sources from Scopus and Web of Science, which may not necessarily cover all the scholarly sources on AI adoption in higher education in the existing literature. The sources for the current research are restricted to Scopus and WoS up to July 22, 2024. Further studies can expand on AI integration into higher education by employing other databases. Moreover, one of the main limitations is that bibliometric analysis does not provide a rich qualitative analysis of the problem, including factors such as the perceptions of educators and students. Future research should build on these findings using a mixed-methods approach to examine participants’ perceptions and understanding of AI use in learning environments. Moreover, longitudinal studies could document changes in the topics across the years and evaluate the effects of the advancements in AI technologies on learning and teaching practises and achievements.

Ethics Committee Approval: As this study is based entirely on a review of existing literature, rather than primary data collection, ethics committee approval was not required. The analysis and synthesis of previously published research do not involve new interactions with human subjects or require ethical clearance.

Peer-review: Externally peer-reviewed.

Conflict of Interest: The authors have no conflict of interest to declare.

Grant Support: This research has been partially supported by the Erasmus+ Programme under the project titled 'Empowering Educators for AI-Integrated Learning' (Project ID: 2023-2-TR01-KA220-HED-000185020).

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