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Visualizing the Dual Landscape of Artificial Intelligence in Higher Education: A Multimethod Systematic Review and Bibliometric Analysis

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ABSTRACT

The Higher Education sector is being revolutionized by AI, with machine learning, natural language processing and generative AI applications. Yet, with the fast pace of technological evolution, both the possibilities and threats of AI incorporation have been spread out. This study includes an integrated multimethod systematic review and bibliometric analysis of the dual landscape of AI in higher education. Following PRISMA 2020 guidelines, systematic searches of Web of Science (n=1,631), PubMed (n=1,349), and Scopus (n=1,439) yielded 4,419 records (2021-2025). Following screening for duplication and eligibility, 110 studies (85 high and 25 medium quality) were included for thematic synthesis. A concurrent bibliometric analysis of 1,227 documents in Scopus was performed to depict author citation networks, keyword co-occurrence, and bibliographic coupling by source and country, using VOSviewer. The study identified Jiao, Ouyang, and Zheng as the most cited authors; the most frequently used keywords are 'ChatGPT' (173 times) since late 2022. Academic support, automated grading, teacher development, perceived usefulness, personalization of learning, and prediction of performance. The perceived ease of use, 24/7 access to technology, administrative efficiency; and academic integrity, data issues, integration barriers, technological limitations, equity concerns. And attitudinal barriers were identified as opportunity and challenge domains, respectively, during the thematic synthesis process. This study offers a dual landscape framework which means that there are no opportunities without challenges, and no challenges without opportunities. It delivers an evidence-based typology for institutional AI strategy, and priority areas for policy intervention, practically. The methodologically, it shows the usefulness of the combination of bibliometric and systematic review for complete literature synthesis. This research aims to explore the opportunities and challenges in integrating AI into higher education, based on a systematic review and bibliometric analysis of relevant literature.

Keywords: AI integration, opportunities, challenges, systematic review, bibliometric analysis

INTRODUCTION

Artificial Intelligence (AI) is defined as the branch of computer science which aims at developing systems that perform tasks carried out by human beings due to their intelligence (Schmidt et al., 2025). AI may come in many varieties, such as narrow AI, which is restricted to perform only limited tasks in a particular domain, or even general AI that learns to complete more complex tasks from diverse cognitive perspectives. The application of AI may be found in different industries like healthcare, education, transportation, entertainment, and others. However, the primary goal of using artificial intelligence is to enhance performance while ensuring accurate job completion in respective spheres (Abubaker et al., 2025; Chen & Anyanwu, 2025; Schmidt et al., 2025). It is worth mentioning that core artificial intelligence tools such as machine learning, natural language processing, and generative AI have become widely utilized in the context of enhancing pedagogic practice and administrative operations in the education sphere (Schmidt et al., 2025; Tebenkov & Prokhorov, 2021; Villegas-Ch et al., 2020). Indeed, it becomes possible due to the fact that the technologies related to artificial intelligence significantly influence all spheres of our lives nowadays (Kidega et al., 2026). The use of artificial intelligence technologies in the education sector has impacted how institutions work and what methods are used in administration, instruction, and teaching and learning. One of the greatest achievements of AI in the field of education has been the advancement and improvement of accessibility in education. With the help of AI technology, the issue of inequality in education can be solved by providing online learning options and customizing education, as mentioned by Fahimirad and Kotamjani (2018). Additionally, there have been sociotechnical transformations brought by AI that necessitate the need for careful adoption of the strategies and models (Bearman & Ajjawi, 2023; Bearman et al., 2023). Because of this, it is possible that changes will occur in how teaching will be done in institutions and how communication will be carried out between instructors, administrators, and students. It will change not only the role of education design but also the power of decision-making from institutions to teachers and students. Nevertheless, with the emergence of new technological advancements in education, AI has gone beyond academic research and is now becoming a critical component in the education training process (Ciecierski-Holmes et al., 2022; Holmes et al., 2023). Therefore, the change necessitates looking at the issue of curricula as an educational process and recognizing it as an essential part of the education system in the era of artificial intelligence. Since the COVID-19 pandemic began, the swift move towards the online mode of education took place in higher education institutions, and remote learning became commonplace (Kim & Kim, 2022). Nevertheless, the transformation of the higher education system from offline to online learning started well before the pandemic, owing to technology development (Xu & Ouyang, 2022). In the current scenario, among all the developments in education, the application of artificial intelligence (AI) has been more impactful in comprehending and analyzing responses (Makridakis, 2017). Think about the development or integration of AI technologies and their applications in connection with the enhancement of EMIS. There is an improvement in the collection and processing of data, making the administration and delivery of education more equal, inclusive, transparent, and personalized (UNESCO Publishes Beijing Consensus on Artificial Intelligence and Education - Ministry of Education of the People's Republic of China, 2019). The adoption of AI technologies in the field of education has been identified as a priority in the global context in several ways. First of all, the European Digital Competence Framework has been transformed into the European Digital Education Content Framework, which includes skills in terms of AI and data (Digital Education Action Plan) (2021-2027). AI education was considered one of the strategic components in relation to human capital development goals in the National AI Strategy, as described in a report published by the Ministry of Digital Development, Singapore (Ministry of Digital Development. Singapore Smart Nations, 2024).

Research Gap and Problem Statement

Despite the many research efforts and studies carried out on the part of AI in Educational Technology, the current studies are dispersed in two important aspects. Most of the reviews that have been carried out to date have been either bibliometric, for 'mapping' the research field and/or systematic, for summarizing particular applications, with only a few reviews combining both approaches to provide an overview of both the intellectual structure of the field and its substantive research results. Second, the advent of generative AI technology, particularly ChatGPT, at the end of 2022, has shifted the landscape of AI in higher education, making some of the earlier reviews somewhat outdated both in terms of the technology and the challenges of AI. The purpose of this study is to close these gaps by employing the multimethod approach of bibliometric mapping together with systematic and thematic literature synthesis of the literature, covering the timeframe of 2021–2025, to cover the transformative effect of the recent technological developments. This dual landscape framework approach of opportunities and challenges allows for a balanced understanding of opportunities and challenges at the same time.

THEORETICAL FRAMEWORK

This research is based on three complementary theories. The Technology Acceptance Model (TAM; Davis, 1989) provides a lens to explore the acceptance and views of educators and students on using AI in educational contexts through perceived usefulness and perceived ease of use. The authors used the Technology Acceptance Model (TAM; Davis, 1989) to gain insight into the educators' and students' perceptions and acceptance of the use of AI in educational contexts from a perspective of perceived usefulness and perceived ease of use. Opportunities are classified based on the TAM and identified as accessible (perceived ease of use) or personalized (perceived usefulness). Moreover, there is the introduction of the concept of AI from the perspective of the education paradigm framework, according to Xu and Ouyang (2022). As mentioned by the authors above, there are three types of paradigms associated with AI applications within education: first, AI directed where the learner acts as the receiver of the instructional process delivered by AI; second, AI supported where the learner acts as an accomplice in the use of AI; and third, AI empowered where the learner acts as a leader using AI as tools for creating knowledge. Third, a sociotechnical systems theory (Bostrom & Heinen, 1977) highlights the need to consider the interconnection and interaction between technical subsystems and social subsystems. This lens will assist us in examining the technical capacity and the institutional, pedagogical, and cultural influences that shall impact the use of AI in higher education.

Contribution Statement

This research uniquely contributes to the field of AI in Higher Education in the following ways: First, this study is a combination of the two approaches used in other reviews such as the bibliometric approach or systematic approach, but not both as is done in other reviews (e.g., Bond et al., 2024; Zawacki-Richter et al., 2019), which would help to represent the intellectual structure of the field at a macro level and synthesize substantive results at a micro level. Second, the review's scope is limited to the time period of 2021-2025, which will ensure the review draws from a period that has been impacted by transformative generative AI technologies, including ChatGPT, and avoids previous reviews that were conducted prior to this inflection point.

The term “dual landscape” in this research implies the simultaneous presence of transformational opportunities and challenging aspects related to AI application in higher education. These opportunities may include AI-based assessment tools, adaptive teaching methods, administrative efficiency gains, personalized learning strategies, and greater educational accessibility through AI applications. Threats to academic integrity, data privacy issues, algorithmic bias, the digital divide deepening educational inequity, a lack of AI literacy among educators, negative attitudes toward AI, and a lack of all-inclusive policies and ethical guidelines for the use of AI pose challenges. This duality is paramount when developing a strategy that maximizes the use of AI and, importantly, minimizes potential risks. This framing recognizes that opportunities and challenges are not merely separate categories but are often interdependent; for instance, automated assessment systems that improve grading efficiency may simultaneously create new vulnerabilities for academic dishonesty, requiring holistic rather than piecemeal policy responses

Research Questions

This study is guided by five research questions:

RQ1. Who are the most influential authors shaping the intellectual structure of AI integration in higher education, and what characterizes their collaborative networks?

RQ2. What keyword patterns and thematic concentrations define the evolution of AI in higher education research from 2021 to 2025?

RQ3. In which publication venues and countries is research on AI integration in higher education predominantly disseminated, and what does this geographic distribution reveal about the global research landscape?

RQ4. What opportunities and challenges constitute the dual landscape of AI integration in higher education?

RQ5. What strategies and solutions have been proposed in the literature to address the identified challenges of AI integration?

Rationale for Multimethod Design

The rationale behind using bibliometric analysis and systematic review in this study lies in their unique strengths in analyzing data at different levels. While bibliometric analysis offers macro-level analysis of the intellectual structure of a field and its knowledge production processes. By identifying leading authors, keywords, publications, journals, and geographic regions in which the research is carried out (Donthu et al., 2021). Systematic review helps identify specific opportunities and strategies at the micro level through careful thematic analysis of primary study findings (Grant & Booth, 2009). Thus, this research allows combining a broad overview of research trends in the field based on bibliometric findings and their in-depth analysis based on specific findings obtained using a systematic review. The bibliometric analysis in this study used only the Scopus database due to its coverage of literature in the field of education and computer science, and compatibility with the software VOSviewer that helps visualize data. The systematic review in this study was performed using three databases: PubMed, Web of Science, and Scopus. This integrated design responds to calls for multimethod approaches in educational technology research (Grant & Booth, 2009) and addresses the inherent complexity of examining AI integration from multiple analytical perspectives.

Firstly, the study adopted the bibliometric analysis, which was conducted on 16 December, 2025, by selecting all disciplines (fields)in Higher education in Scopus with the keywords "Artificial intelligence, Integration, higher education." 1227 documents (studies) met the initial keyword screening process with related words. The data were transferred from Scopus as a CSV file and analysed using VOSviewer software version 1.6.20. During data analysis, the analysis was restricted to author citations, co-occurrence of all keywords, Bibliographic coupling of documents, Bibliographic coupling of sources, and Bibliographic coupling of countries (Paraschiv et al., 2024). The selection of these criteria aimed to determine which keywords the authors working on artificial intelligence integration in Higher education use, where they publish (sources), and in which countries they publish

Secondly, the study used a systematic literature review, meticulously following the protocols established by Grant and Booth (2009), as well as the Cochrane Handbook for Systematic Reviews (Sterne et al., 2019) and the PRISMA recommendations (Bond et al., 2024; Kangwa et al., 2025a; Moher et al., 2009; Page et al., 2021).

The study followed a six-step methodology: establishment of the research team, selection of the protocol, thorough search for relevant studies aligned with the research objectives, screening and selection of suitable studies, data extraction and analysis, and reporting and dissemination of the results. Moreover, the PRISMA framework directed the sample methodology (Page et al., 2021; Topali et al., 2025) should include research that focuses on the integration of AI in higher education. The research on the potential and constraints of integrating AI into higher education is done using bibliometric analysis. Consequently, **Table 1** shows the boundaries for the questions asked in the study and the initial coding process (Msambwa et al., 2024; Sterne et al., 2019). **Table 1** maps five research questions to coding criteria: RQ1-3 use bibliometric coupling (authors, keywords, sources); RQ4 uses thematic categorization for opportunities and challenges; RQ5 uses thematic categorization

METHOD

Search Strategy

Only peer-reviewed research articles were utilized in the search and analysis to augment the reliability and validity of the examined data and results (Page et al., 2021). The study was confined to publications from 2021 to 2025 to encompass all recent works and advancements in AI integration, owing to the swift progression of technology (Kangwa et al., 2025a).

Search Strings and Terms

Keywords and phrases were carefully applied in electronic databases such as Web of Science, PubMed, and Scopus. In addition, the search process was carried out using the PRISMA approach, whereby scholars employed snowball sampling to find more relevant literature (Kangwa et al., 2025a). The principal search phrases encompassed "integration of artificial intelligence (AI) in higher education," "opportunities of AI integration," "challenges of AI," and "strategies of AI in higher education," along with many refined combinations of these key terms as presented in **Table 1**. The literature search was last performed and updated on December 28, 2025. The search terms were derived from (Kidega et al., 2025) and included the initial search string of terms indexed by the chosen databases for AI integration. As such, the search strings entailed a mix of search terms and phrases, as indicated in **Table 2**. Through the search strategy, 4419 articles were found (**Figure 1**), and all were subject to further scrutiny (Kangwa et al., 2025a; Page et al., 2021). **Table 2** shows systematic review search strings organized into three categories: technology terms (AI, machine learning, chatbots), higher education settings (universities, colleges), and opportunity/challenge terms (benefits, barriers, strategies). The search strings in **Table 2** were adapted for each database's syntax requirements:

Table 1. Scope and Code Procedure

Research Questions	Scope	Initial Coding Criteria
RQ1: Most influential authors in AI integration	Identify frequently cited authors and their collaborative networks	Bibliographic coupling by authors, citations analysis, total link strength
RQ2: Dominant keyword patterns	Ascertain thematic concentration and evolution of the field	Co-occurrence coupling by all keywords; cluster analysis
RQ3: Publication venues and countries	Examine where research is published and by which countries	Bibliographic coupling by sources; bibliographic coupling of countries
RQ4: Opportunities and Challenges	Identify and categorize opportunities and challenges of AI integration	Thematic categorisation: inductive coding of opportunities and challenges and from included studies
Strategies and solutions	Identify proposed solutions to AI integration challenges	Thematic categorisation: inductive coding of strategies and solution from included studies

Table 2. Terms and Search Strings

Terms	Search Strings
Technology (AI & ML), AI integration	"Artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "natural language processing" OR "NLP" OR "chatbot" OR "intelligent tutor system" OR "generative AI" OR "large language model" OR "LLM" OR "learning analytics" OR "educational data mining" OR "integration")
Higher education	"Higher education" OR "universities" OR "college" OR "tertiary education" OR "post-secondary education" OR "undergraduate" OR "graduate education" OR "graduate school"
Opportunities, challenges, strategies	"opportunities" OR "prospect" OR "benefit" OR "advantage" OR "potential" OR "challenges" OR "barrier" OR "obstacles" OR "risks" OR "limitations" OR "difficulty" OR "strategies" OR "solutions" OR "recommendation" OR "policy" OR "frameworks" OR "future directions"

Scopus: TITLE-ABS-KEY ((“artificial intelligence” OR “AI” OR “machine learning” OR “chatbot” OR “generative AI” OR “college”) AND (“opportunities” OR “challenges” OR “strategies”)) AND PUBYEAR>2020 AND PUBYEAR< 2026 AND DOCTYPE (ar)

Web of Science: TS=((“artificial intelligence” OR “ AI” OR “machine learning” OR “chatbot” OR “generative AI”) AND (“higher education” OR “universities”) AND (“opportunities” OR “challenges”)) AND PY=(2021-2025) AND DT=(Article)

PubMed: ((“artificial intelligence” [Title/Abstract] OR “AI” [Title/Abstract] OR “machine learning” [Title/Abstract] Or “chatbot” [Title/Abstract] OR “generative AI” [Title/Abstract] AND (“higher education” OR “universities” [Title/Abstract] OR “college” Title/Abstract AND (“opportunities” [Title/Abstract] OR “challenges” Title/Abstract OR “strategies” [Title/Abstract])) AND (2021: 2025[pdat]) AND (article[filter])

Screening and Eligibility Criteria

A total of 4,419 papers were found using the database searches performed. Inclusion of the articles outside the publication year range (2021 to 2025), failure to be peer-reviewed, and duplicates (Kangwa et al., 2025a, 2025b; Kidega et al., 2026; Yvan et al., 2026) were done through the use of the following procedure. Two evaluators (KC & ACL) independently examined the 2,332 non-duplicate articles based on the inclusion-exclusion criteria provided. Inter-rater reliability was calculated through percentage agreement and Cohen’s κ coefficient. Percentage agreement between the two raters stood at 95% (2,215 agreements out of 2,332). Cohen's κ was 0.89 (95% confidence interval: 0.86-0.92), which is defined as 'substantial to almost perfect' (Landis & Koch, 1977). Disagreements were resolved until there was agreement, which resulted in 100% agreement on the final selected articles. After the initial selection phase, 392 papers were chosen for full-text analysis, presented in **Table 3**.

Data Extraction

The search results were obtained from various databases, including Scopus, PubMed, and Web of Science, and then consolidated into a single Excel file. Subsequently, data purification was executed, and redundancies were eliminated (Kangwa et al., 2025a; Kidega et al., 2025). Subsequent to the elimination of duplicates, the eligibility of the residual records was assessed via an independent review of their titles and abstracts by the researchers to facilitate forthcoming full-text screening (Kangwa et al., 2025a). The discrepancies in the independently selected publications were assessed to achieve agreement among the researchers according to the set qualifying criteria. This technique guaranteed full interrater reliability for the inclusion and exclusion criteria, resulting in the selection of 392 studies. Table 3 presents the inclusion and exclusion criteria applied during the screening process. The number of papers rejected because the full text was not available was 242, leaving a total of 110 papers that were evaluated for eligibility (Kangwa et al., 2025b; Yvan et al., 2026).

Table 3. Inclusion and Exclusion Criteria

Criterion	Inclusion	Exclusion
Language	Research Articles in English	Articles not published in English
Publication Type	Peer-reviewed full research articles	Review articles, books, book chapters, editorials, meeting abstracts, data papers, dissertations, preprints, and conference abstracts
Quality Score	High or medium-quality appraisal score	Low-quality appraisal score
Full-text Availability	Full text retrievable	Full text not available
Electronic Database	Indexed by PubMed, Web of Science, Scopus	Not indexed by these databases
Date of Publication	Published between January 2021 and December 28, 2025	Published before January 2021 or after December 28, 2025
Setting	Higher education, college	Other than higher education
Scope	Focus on AI integration, opportunities, challenges.	Not focused on these aspects

Table 3 presents the inclusion and exclusion criteria applied during the screening process. The number of papers rejected because the full text was not available was 242, leaving a total of 110 papers that were evaluated for eligibility (Kangwa et al., 2025b; Yvan et al., 2026).

Quality Appraisal

JBI Critical Appraisal Checklist for Systematic Reviews and Research Syntheses (Aromataris et al.,2015) was used independently by two researchers (KC &ACL) to conduct the quality appraisal. All items were scored on each study using the checklist, and the results were categorized as high, medium, or low quality (with ≥8 meeting the criteria considered high quality, 5-7 considered medium, and <5 considered low quality). Initial independent ratings were compared, and differences discussed with a third researcher (Author 4). After this consensus process, the 85 studies were considered high quality, the 25 medium quality, and the 40 low quality. One hundred ten studies were included in the final review, after discarding 40 low-quality studies. Of the 150 studies initially agreed, there was an interrater agreement of 88% prior to consensus discussion, and a Cohen's kappa of 0.84 (95% CI 0.79–0.89) for the quality classifications. Post-discussion consensus was 100%.

Data Synthesis

Data synthesis in the present study utilized an exhaustive approach of data synthesis consisting of thematic and narrative approaches in a systematic manner of two steps. Data synthesis procedure started with the step of familiarization with the data, followed by the coding process, searching for relevant studies, reviewing those studies, defining and labeling the topics, and finally compiling the synthesis in a comprehensive report (Aromataris et al., 2015; Lockwood et al., 2015). Narrative synthesis was then applied to prepare a preliminary synthesis through analysis of relationships within and among different studies, assessing the robustness of the synthesis, providing summaries of the synthesis, discussing findings in the context of past literature and theory, and drawing conclusions with appropriate recommendations (Aromataris et al., 2015; Lockwood et al., 2015). Consequently, the exhaustive approach helped compile an exhaustive synthesis to offer exhaustive insights into the impact of AI technology in higher education in developing countries, as shown in **Table 3**. **Table 4** shows a three-step validation process: independent coding by researchers, synthesis of harmonized themes, and supervisor verification of theme accuracy.

Table 4. Summary of the Coding Procedure

Step	Action
Independent Coding	Researchers independently coded the data.
Synthesis of Codes	Harmonized themes were synthesized from the independent codes.
Verification	The supervisor verified the themes for accuracy.

Initial Coding and Thematic Procedure

The scope and thematic coding process to address the objectives and research questions of this study are summarised in **Table 5**. The thematic synthesis followed a six-phase reflexive thematic analysis framework (Braun & Clarke, 2006). In Phase 1, researchers familiarized themselves with the data through repeated reading of the 110 included studies. For instance, in Phase 2, initial codes, including automated essay scoring, providing immediate feedback, language test automation, and plagiarism detection programs, were developed separately by the three researchers (KC, ACL, & ECI). These codes in Phase 3 were consolidated into potential themes. The above-mentioned codes related to assessment in AI applications were categorized as the sub-theme Automatic Grading Systems, which falls under the larger theme Academic Support. Likewise, codes such as facilitating cheating using ChatGPT, worries about contract cheating, issues regarding detecting originality, and vulnerabilities in assessment were categorized under the sub-theme Academic Integrity within the Challenges theme.

The themes generated during Phases 4 and 5 were cross-checked with coded data extracts and the complete data sets for consistency. Themes in Phase 5 were further revised, defined, and named after deliberation between all researchers. Finally, in Phase 6, a report containing all findings was produced, and the entire thematic framework was validated by the fourth researcher (FS). Any discrepancies in theme interpretation or code assignment were resolved through discussion until full consensus was achieved among all four researchers, ensuring the trustworthiness of the thematic synthesis. Thematic analysis in **Table 5** maps research questions to opportunity themes (Academic Support, Perceived Usefulness, Perceived Ease of Use) and challenge themes (Academic Integrity, Data Issues, Understanding Gaps, Integration Barriers, Digital Divide, AI Literacy) with corresponding codes.

Table 5. Summary of Thematic Codes and Analysis

Research questions	Themes	Codes
Opportunities	Academic Support	Resource Availability, Training, Technical Guidance, Automatic grading system, Teacher professional development, Pedagogical proficiency
	Perceived usefulness	-Learning Enhancement, Skill Development -Prediction of student performance
	Perceived ease of Use	Accessibility, User-Friendliness, Enhancing the efficiency of Mgt tools, Adaptive teaching proficiency
Challenges	Academic integrity	-High rates of cheating, Academic dishonesty, Plagiarism, No clear assessment criteria, ethical constraints, Replacement by AI, insufficient students' data, Data privacy
	No suitable data for AI predictive model	Lack of comprehensive understanding of AI technologies, Lack of institutional support, No clear guidelines on assessment,
	Insufficient integration of AI technologies in HE	Limited knowledge on AI usage, Technological advancement at HEIs, limited languages, Lack of universal discipline defined by AI
	Insufficient multidisciplinary AI technologies for Education	Not optimal objectives, Lack of pedagogical expertise, Inadequacy of AI tools
	Educational fairness (Digital divide)	Lack of transparency/fairness, Worsening education inequity, Lack of transparency
	Inadequate comprehension of AI technologies	Limited knowledge on the AI usage, Insufficient AI literacy, Negative Attitude towards AI

Results Synthesis Procedure

Table 5 systematically associates the study subjects with their corresponding themes, codes, and synthesis stages. Opportunities afforded by the use of AI in higher education institutions, emphasising academic assistance, perceived usefulness, and perceived user-friendliness, with related areas such as resource availability, learning augmentation, and accessibility.

In addition, difficulties associated with using AI or incorporating AI into their academic programs include academic misconduct, cheating, poor knowledge on how to use AI, integrity issues, behavioral intention, ethical considerations, lack of multidisciplinary AI technologies, and poor knowledge on AI technologies, among others **Table 6**.

All the research questions were subjected to a two-step analysis synthesis to enhance data management (Aromataris et al., 2015; Kangwa, 2025a; Lockwood et al., 2015). **Table 6** compares the two parallel six-step methods for the synthesis of systematic reviews. Thematic Synthesis emphasizes the use of coding, while Narrative Synthesis emphasizes the exploration of the relationship between the findings of the studies and the assessment of the robustness of the findings for the generation of conclusions and recommendations.

RESULTS

The search method yielded a total of 4,419 records from the electronic databases: PubMed (n = 1,349), Web of Science (n = 1,631), and Scopus (n = 1,439). After the removal of 2,087 duplicates, 2,332 records were assessed for eligibility based on their titles and abstracts. Of these, 1,940 records were discarded for not satisfying the qualifying criteria. The full texts of the remaining 392 documents were solicited for inclusion. However, only 110 studies met the criteria for inclusion in this systematic review, as outlined in **Figure 1**. PRISMA flow diagram showing study selection process for AI in higher education review: records identified, screened, assessed for eligibility, and final studies included in synthesis and bibliometric analysis. **Figure 2** shows the trend of AI in education for the last five years according to articles reviewed for this analysis. The table shows publication trends on AI in higher education from 2021-2025. Publications increased steadily from 16 (2021) to 42 (2022), dipped to 15 (2023), then rose sharply to 30 (2024) and 45 (2025), indicating growing research interest despite yearly fluctuations. The list of top-cited authors generated through the bibliometric analysis is shown in **Table 7**. These authors are Jiao, Peng Cheng (3 articles, 482 citations, total link strength 12), Ouyang, Fan (3 articles, 482 citations, total link strength 12), and Zheng, Luyi (2 articles, 480 citations, total link strength 12), demonstrating the highest citation counts and strongest collaborative linkages. The average publication years of these top-cited authors range from 2022.0 to 2023.5, indicating the recency of the most impactful contributions to the field.

Table 6. Two-stage Synthesis Process

Stage 1: Thematic Synthesis	Stage 2: Narrative Synthesis
Familiarizing with the data	Developing a preliminary synthesis
Generating initial codes	Exploring relationships within and between the studies
Searching for themes	Assessing the robustness of the synthesis
Reviewing themes	Presenting the results
Defining and naming themes	Discussion of the results
Producing the report	Conclusions and recommendations

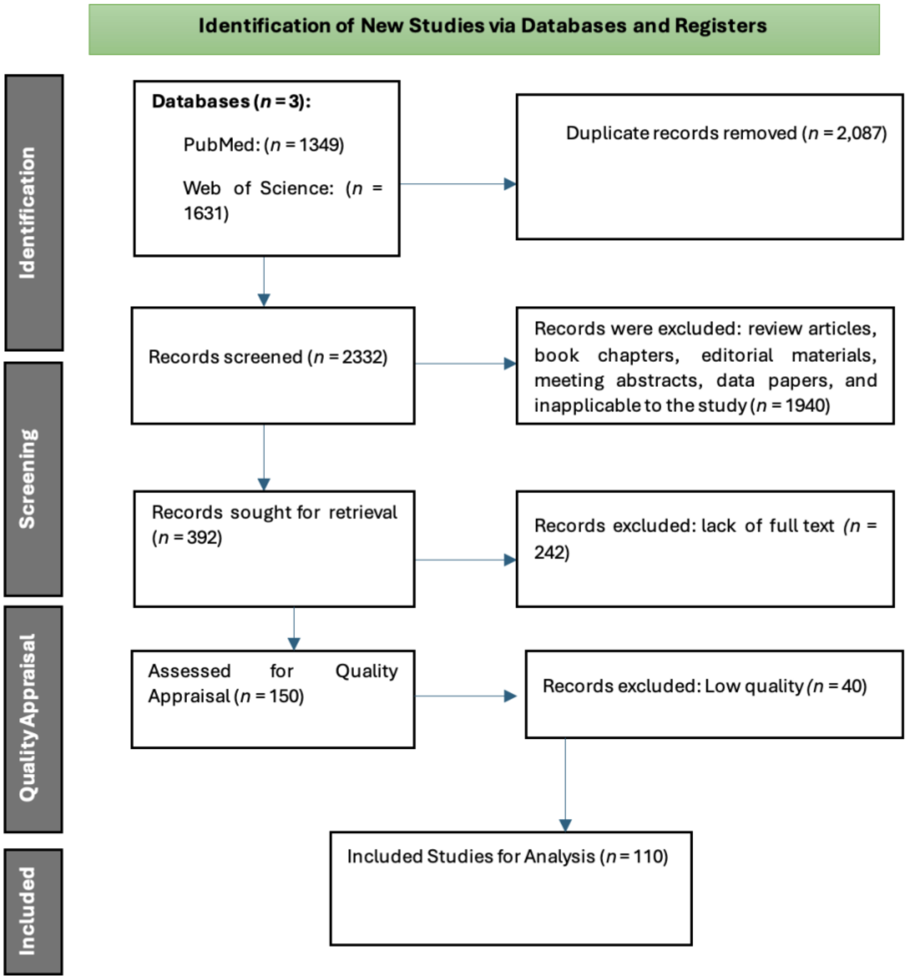

Figure 1. PRISMA flowchart for the Sampling procedure, showing data search, exclusion, screening, and final inclusion of relevant studies (Source: Authors)

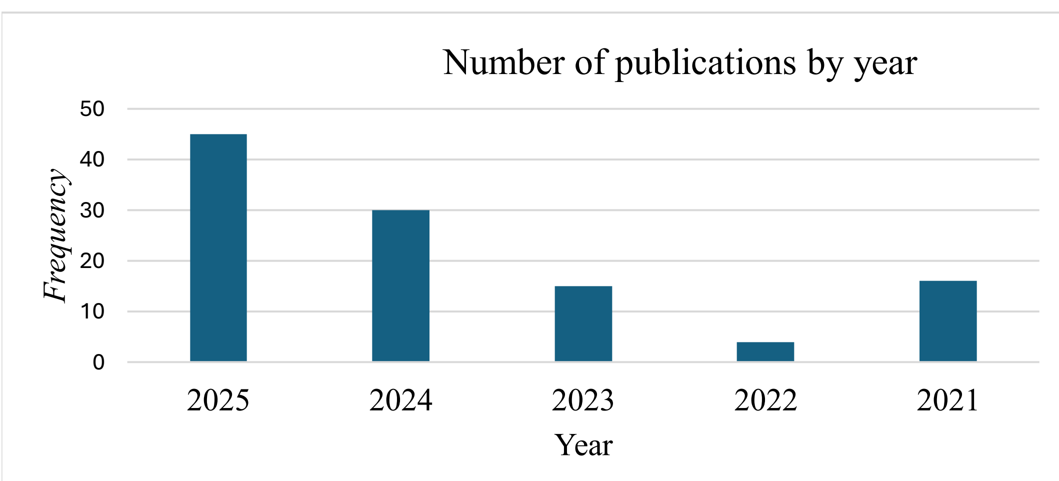

Figure 2. Trends in the documents published 2021-2025, analysis of all the publications for this review, and presented according to their year of publication (Source: Authors)

Table 7. Citation of authors

Author	Documents	Citations	Total Link Strength	Avg.Pub. Year
Jiao, Peng Cheng	3	482	12	2023.00
Ouyang, fan	3	482	12	2022
Zheng, Luyi	2	480	12	2022.50
Marengo, Agostino	3	170	4	2023.67
Pange, Jenny	2	169	4	2023.50
Pagano, Alessandro	2	169	4	2023.50

Co-Occurrence- All Keywords

Figure 3 was generated with the help of VOS viewer for the co-occurrence of all keywords. The nodes represent the keywords, and the thread-like structure represents the links between the keywords. In **Figure 3**, the analysis and counting methods were selected as co-occurrence with all the keywords in the VOS viewer to answer the research question (RQ2). The co-occurrence analysis parameters were set at a minimum threshold of 10 occurrences per keyword. Of the 5,548 unique keywords identified across the dataset, 135 met this threshold. These keywords were organized into 11 thematic clusters with 13,302 links and a total link strength of 32,028. **Table 8** presents the keywords with the highest occurrence frequencies and their respective clusters.

The most common keywords included “artificial intelligence” (641 mentions, Cluster 1) and “higher education” (401 mentions, Cluster 4), reflecting the research topic of the paper. The term “ChatGPT” was mentioned 173 times (Cluster 5), which is relatively high considering its release in the public domain only in late 2022. Other terms that occurred often included “contrastive learning” (127 mentions, Cluster 3), “education” (96 mentions, Cluster 2), “curricula” (87 mentions, Cluster 1), and “AI” (55 occurrences, Cluster 2), also demonstrated high frequencies. The distribution of keywords across 11 clusters suggests distinct research sub-communities, with Cluster 1 (AI, curricula, integration) emphasizing implementation-focused research and Cluster 5 (ChatGPT, generative AI) representing the recent surge of interest in large language models.

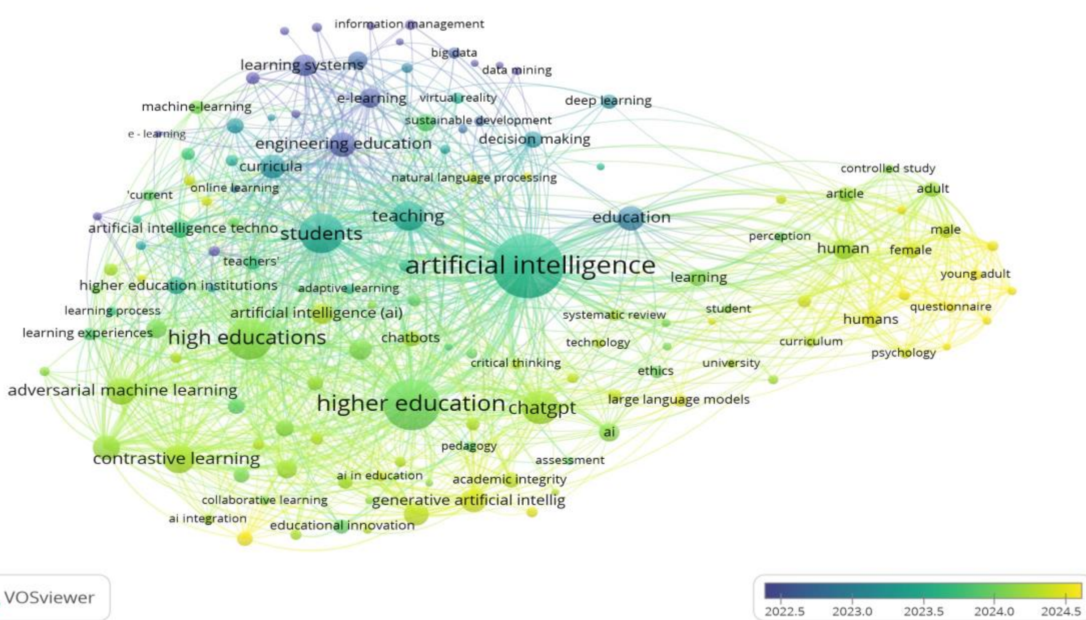

Figure 3. Bibliometric finding on Co-occurrence (Source: Authors)

Table 8. Co-occurrence keywords

Keyword	Occurrences	Links	Total link strength	Cluster
Artificial Intelligence	641	134	3036	1
Higher education	401	128	1821	4
Artificial Intelligence (Ai)	66	76	291	5
curricula	87	93	620	1
Integration	36	75	247	1
Universities	13	45	106	2
Contrastive learning	127	95	1062	3
Ai	55	88	283	2
Education	96	119	552	2
ChatGPT	173	123	851	5

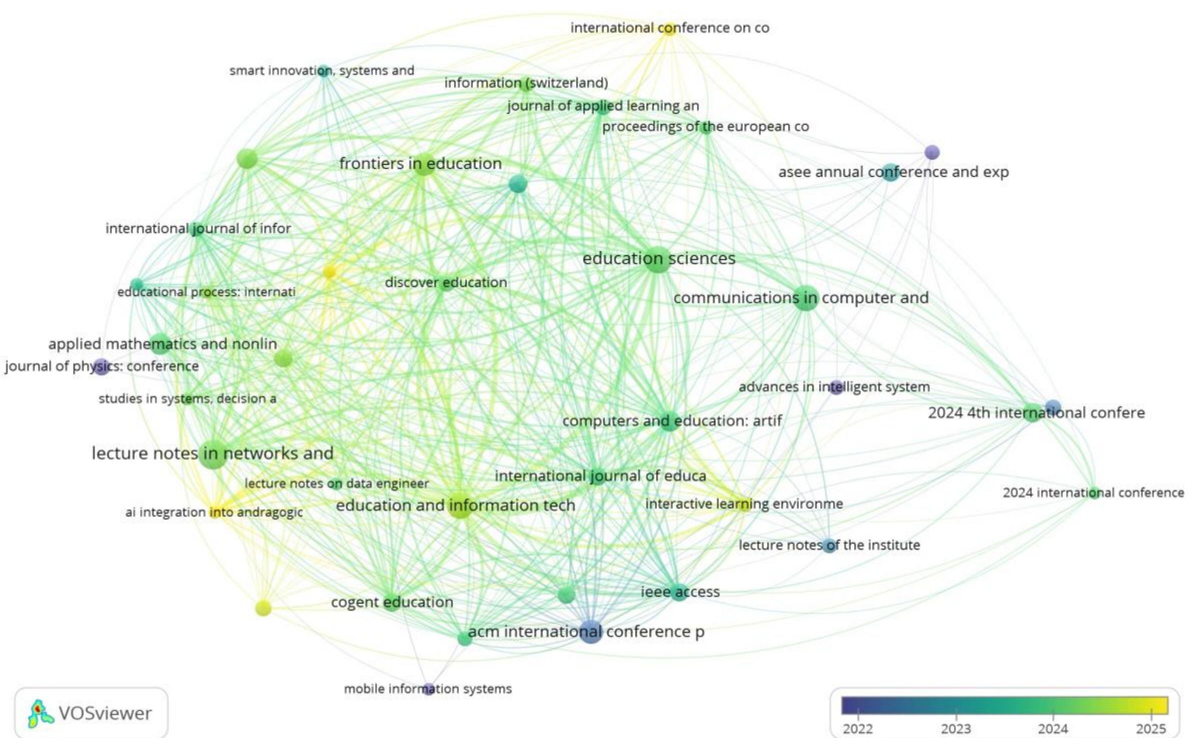

Figure 4. Bibliographic coupling of sources (Source: Authors)

The presence of conference proceedings (e.g., *Lecture Notes in Computer Science*) indicates that computer science perspectives remain well-represented alongside education-focused publications.

Bibliographic Coupling of Countries

The third analysis, the type of analysis and counting methods with VOS viewer, was chosen as the Bibliographic coupling of countries. Minimum number of documents of a country (10), minimum number of citations of a country (Sánchez-Núñez et al., 2020). Of the 120 countries, 42 meet the threshold with the maximum number of countries per document (25). For each of the 42 countries, the total strength of bibliographic coupling links with other countries was calculated, and 17 countries possessed the greatest link strength. 17 Seventeen generated 3 clusters, 190 links, and a total link strength of 60668.

Figure 5 identified 42 countries meeting the threshold of a minimum of 10 documents. China and the United States demonstrated the highest total link strengths, indicating that research outputs from these countries are frequently cited within this dataset. The United Kingdom, United Arab Emirates, Australia, and Saudi Arabia also showed substantial link strengths. However, one should be aware that the presented results may have some limitations. For example, the use of English databases (Scopus, Web of Science, PubMed) can result in underrepresentation of studies in non-English speaking regions, while numerous citations can reflect the popularity rather than the quality of research. The classification of the countries into three groups can be viewed as an indicator of the existence of cooperation networks among the countries with similar research interests, a common language, and financial support. The presence of keywords such as 'ChatGPT' and 'curricula/integration' in the network can reflect the current trends in the field of study.

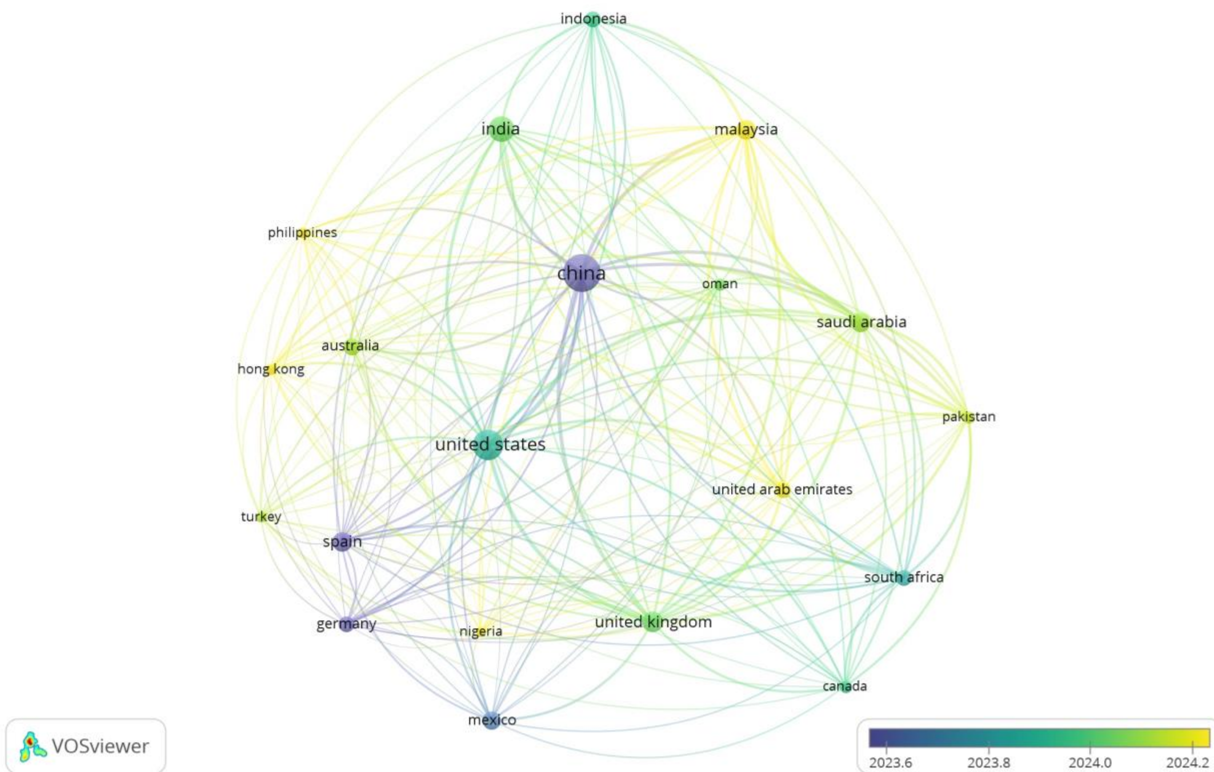

Figure 5. Bibliographic coupling of countries (Source: The authors)

Results on RQ.4

Integrated Synthesis: Connecting Bibliometric and Thematic Findings

The multimethod design reveals four convergent patterns. First, keyword co-occurrence (**Figure 3**) shows 'ChatGPT' (173 occurrences) and 'academic integrity' terms cluster together. This directly aligns with the thematic finding (**Table 10**) that academic integrity is the most frequently discussed challenge, suggesting the emergence of ChatGPT has driven research attention toward integrity concerns. Secondly, the results of bibliographic coupling by country (**Figure 5**) reveal the dominance of China and the USA in publishing papers on automated assessment and performance prediction; the thematic synthesis also indicates that these two countries generate most of the research related to automated assessment and performance prediction. On the other hand, research on issues such as equality and the digital divide comes from India, Indonesia, and African countries.

Table 9. Opportunities of AI integration in Higher Education

Theme	Sub-theme	Codes	Representative studies
Academic support	Assessment	Automatic grading systems, automated feedback, formative assessment tools	(Fahimirad & Kotamjani, 2018; Liang & Bai, 2025; Liu et al., 2023a)
	Teaching support	Resource availability, training materials, technical guidance	(H. Chen & Anyanwu, 2025; Salas-Pilco et al., 2022)
	Professional development	Teacher training programs, pedagogical skill enhancement	(Ghamrawi et al., 2024; Reina-Parrado et al., 2025)
Perceived usefulness	Learning enhancement	Personalized learning pathways, adaptive content delivery, skill development	(Bates et al., 2020; Yu & Lu, 2021)
	Perform prediction	Early warning systems, At-risk student identification, retention strategies	(Costa-Mendes et al., 2021; Durães et al., 2025; Yağcı, 2022)
Perceived ease of use	Accessibility	24/7 availability, multiple device access, language support	(Khan & Alotaibi, 2020; Villegas-Ch et al., 2020)
	Administrative Efficiency	Automated scheduling, Library services enhancement, Decision support systems	(Baek et al., 2024; Gomez & Ruipérez-Valiente, 2022; Ruiz Rodríguez et al., 2025a)

Table 10. Challenges of AI in Higher Education

Theme	Codes	Representative studies
Academic integrity	Cheating, plagiarism, Academic dishonesty, unclear assessment criteria	(Coates et al., 2025; Eaton, 2021; Munaye et al., 2025; Sullivan et al., 2023)
Data challenges	Unsuitable data for AI models, insufficient student data, data privacy concerns	(Bozkurt, 2019; Costa-Mendes et al., 2021; Yu & Lu, 2021)
Integration barriers	Limited understanding of AI technologies, lack of institutional support, no clear assessment guidelines	(Ahmed & Hamdan, 2024; Durães et al., 2025; Kim & Kim, 2022)
Technological limitations	Insufficient multidisciplinary AI tools, slow technology advancement, limited language support	(Borenstein & Howard, 2021; Chiu, 2021; Chiu et al., 2023., Ruiz Rodríguez et al., 2025b)
Equity concerns	Digital divide, lack of transparency/fairness, worsening educational inequity	(Baek et al., 2024; Khan & Alotaibi, 2020; Salas-Pilco et al., 2022)
Attitudinal Barriers	Limited AI literacy, Negative attitudes, anxiety, reduced self-efficacy	(Alghamdi et al., 2020; Gupta & Khosla, 2021; Gupta & Bhaskar, 2020; Wang et al., 2024)
Research gaps	Limited socio-emotional focus, Absence of educational perspectives, ineffective evaluation methods	(Renz & Hilbig, 2020; Salas-Pilco et al., 2022; Trisnawati et al., 2023)

Thirdly, the three clusters obtained in source coupling include: (a) education technology journals, (b) AI in education journals, and (c) computer science proceedings. The above classification is an indicator of the existence of different intellectual sources within the field that often fail to interact with each other.

Fourth, the temporal pattern in Figure 2(publications dipping in 2023 then rising sharply) coincides with ChatGPT's release (November 2022), suggesting a "ChatGPT effect" that bibliometric keyword analysis confirms and thematic synthesis substantiates through the predominance of integrity-related codes in 2023-2025 publications.

DISCUSSION

Influential Authors and Collaborative Networks

Analysis of author citations shows that this is a field in its relative infancy and dominated by a small cohort of highly influential researchers. As it is evident from **Table 7**, authors such as Jiao, Peng Cheng, Ouyang, Fan, and Zheng Luyi present very high citation counts considering the number of documents they have published, meaning their recent works have gained considerable attention and impact immediately. The analysis of the common source of citations for different works individuates a higher number of citations for Jiao Peng Cheng. He is a professor at Zhejiang University in Hangzhou, China, who has published many articles and has many citations and a case in point is the "Artificial intelligence in online higher education: A systematic review of empirical research from 2011-2020" Together with his co-author F. Ouyang, with whom he worked in most of the publications "artificial intelligence in Education: thee paradigms". These paradigms include; AI directed students as recipient which is under behaviorisms, AI -supported learner as collaborator that is cognitive social constructivism, and thirdly, AI empowered learner as leader that is constructivist complex adaptive system.

The high average publication year, ranging between 2022-2023 for these top-cited authors, indicates the recency of the most impactful works, probably due to the explosive emergence of advanced AI models such as ChatGPT at the end of 2022. This pattern shows what could be described as a "hot" research front where rapid dissemination and citation occur around breakthrough technologies. Figure 1, the network visualization, and the metric of "Total Link Strength, all show us that these influential authors do not stand alone but are part of a collaborating core. This structure is very typical for nascent and high-growth research domains, where key players often co-author and build on each other's works (L. Chen et al., 2020). The strength of links here will imply concentrated dissemination of ideas and, and while it may accelerate development in this field, it runs the risk of creating an echo chamber when not complemented by diversity.

Opportunities

Automatic Grading Systems

The automated grading systems powered by Artificial Intelligence (AI) can grade student workloads, offer feedback, and generate personalized training programs in various content domains (Fahimirad & Kotamjani, 2018; Liang & Bai, 2025; Liu et al., 2023a). These systems facilitate the efficient assessment, providing immediate formative assessment, especially valuable in online-learning environments (Hu & Qiu, 2025; Spatioti et al., 2023). Even with an increasing use of automated grading tools and their possibilities for different disciplines, their uses for other subjects remain few. Lack of measuring scales that can establish the validity of these automated grading tools in different contexts remains unresolved (Çebi & Karal, 2017; Trisnawati et al., 2023).

Educational Competence and Teacher Support

It has been found that AI technologies have been utilized in various subjects to distribute learning materials, solve problems by reading aloud from textbooks, and conduct analysis of the level of involvement of students during classes (Chiu et al., 2023; Jaiswal et al., 2022; S. Wang et al., 2024). However, the lack of knowledge among many educators concerning basic concepts of AI and its ability to deal with the black box effect makes it difficult for them to control the learning process (H. Chen & Anyanwu, 2025; K. P. Gupta & Bhaskar, 2020; Selwyn, 2022).

Teachers' Professional Development

Application of AI by the authors was aimed at helping teachers improve their professionalism in terms of analyzing tests or pedagogical content knowledge in the real time (Ghamrawi et al., 2024; Reina-Parrado et al., 2025). AI as impartial assessors would play a significant role in making teachers more open to receiving feedback (Chiu et al., 2023; Hough, 2023). However, it should be mentioned that there were not many articles about professional development of teachers, and the use of automatic feedback might be unnecessary for experienced teachers (Renz & Hilbig, 2020; Trisnawati et al., 2023).

Prediction of Students' Performance

Predictive capabilities offered by AI technologies proved to be highly efficient for the prediction of the performance of online learners based on their engagement in learning activities, for example, participating in the discussion forums (Т Акмеше et al., 2021; Wang et al., 2023; Yu & Lu, 2021). This has been found to be effective in the distance learning and MOOCs scenario where there is no physical presence of the teacher (Salloum et al., 2024; Tebenkov & Prokhorov, 2021). Difficulties arise in selecting the proper data for the purpose of building prediction models, whereby, student data that have been previously used for statistical analyses do not seem to fit properly for prediction using artificial intelligence technology, nor do the socioeconomic factors (income, scholarship, etc.) reflect adequately the different variables in play (Costa-Mendes et al., 2021; Chiu et al., 2023; Durães et al., 2025; Yağcı, 2022)

Enhancing Management Platforms

Indeed, the implementation of AI technology has expanded the functions of university management tools including library management, e-learning tools, and university management portals (Baek et al., 2024; Jiménez-García et al., 2025; Rodriguez-Ruiz et al., 2025b). In order to achieve secure access, the system is equipped with facial authentication in the examination room and portal management (Khan & Alotaibi, 2020; Liu et al., 2023b). It is worth mentioning that the procedure of course scheduling and the management of staff have been automatized by applying AI technology to improve administrative performance. Also, AI technology allows assessing the probability of students' dropouts, determining the factors influencing students' academic achievements, providing assistance in scheduling courses, and helping with choosing them (Chiu et al., 2023; Luan et al., 2020; UNESCO, 2023). While learning and teaching are vital components of the use of AI in the domain of university administration. It is possible to suggest that they could be viewed as secondary aspects of the AI application regarding learning and teaching due to the questionable reliability of user models used in creating such technology (Chiu et al., 2023; Cukurova et al., 2020).

Challenges in the Utilization of AI in Higher Education

Academic Integrity

Academic integrity was identified as the most prevalent issue found in the literature (**Table 10**). There are many concerns raised regarding the issues associated with academic fraud through plagiarism, contract cheating, and the potential loss of the validity of the assessments, as these are now even more vulnerable to the application of generative AI, like ChatGPT (Coates et al., 2025; Munaye et al., 2025; Sullivan et al., 2023). The public discourses regarding AI show discussions about its use to commit academic dishonesty, which could impact how the students perceived its use and how the institution responds to it (Eaton, 2021; Hashmi & Bal, 2024). According to the literature, students who feel that they are cheated at high levels are more prone to commit academic dishonesty behavior (Huang et al., 2021; Wood et al., 2021). There were suggestions to reconsider the assessment task to make it less reliant on the application of AI to accomplish assessment tasks (Karkoulian et al., 2025).

The Absence of Integration of AI Technologies into Education

These modern AI technologies try to help learners and support their learning process through the use of such AI technologies as AI chatbots and robots (Ahmed & Hamdan, 2024; Kim & Kim, 2022; T. W. Kim et al., 2023). From the analysis of sources, it appears that teachers usually lack an integrated vision of AI technology and how to use it for supporting their teaching activities (Jobin et al., 2019). Some of the specific problems have been mentioned, such as inadequate information on the capabilities of learning analytics (Durães et al., 2025), inadequate information on the possible use of AI in education (Durães et al., 2025), and an unclear understanding of how to apply AI in teaching methods (Yağcı, 2022). For example, should chatbots be used for students' discussions before or after a teaching session? Future studies should explore the roles of teachers in AI-supported pedagogical strategies.

Lack of Multi-Disciplinary AI Technology for Education

AI models designed for a particular academic field may be inadequate for all students since the learning process involves many variables. Although several subfields exist in the area of AI, such as natural language processing, computer vision, and neural networks (Borenstein & Howard, 2021; Bozkurt, 2019; Chiu, 2021; Chiu et al., 2023; Ghamrawi et al., 2024), the implementation is still rudimentary in developing countries. The advancement of AI technology in education has been quite slow (Bates et al., 2020; Nicolae & Nicolae, 2018). Teachers generally use commercially available technologies for teaching, but these technologies may not necessarily be the best fit for their purposes (Okolo et al., 2023). As a result, researchers should develop tools that are transdisciplinary and leverage more advanced AI tools.

Worsening Educational Inequity through Digital Divide among Students

Most of the explored AI research focused on the potential of AI technology to improve student engagement and develop 21st-century skills (Cukurova et al., 2020; Jiménez-García et al., 2025; Wu et al., 2022; Zhang et al., 2025). However, the benefits were mainly felt by the more able and motivated students. Poor planning and development are observed for the AI tools utilized for the purpose of learners' knowledge acquisition. There is also an absence of enough information regarding the proper utilization of AI tools by educators to teach their learners (Chiu et al., 2023). Learners who need more help may become demotivated because of problems that arise in communication with AI tools, as well as because of the absence of suitable learning materials. Future studies should focus on developing an innovative pedagogical approach and use a learning sciences approach as a methodology in designing and implementing algorithms for individualized learning (Abbass, 2019; Kumar & Boulanger, 2020).

AI Technology Knowledge Deficit on the Part of the Instructors

Most instructors understand AI technologies and use them in opaque ways when teaching. This means that they cannot address students' questions about AI technology as why the platforms recommended specific learning materials to them. Moreover, they lack the skills to use AI technology for learning and other academic purposes, such as teaching and evaluation (Salloum et al., 2024). It is important that future research be conducted on the importance of knowing how instructors can apply AI technology for educational purposes.

Negative Perceptions of Students and Teachers towards AI Technology.

Nevertheless, anxiety and self-doubt of students and teachers while interacting with AI technology have been reported in the literature before (Alghamdi et al., 2020; Çebi & Karal, 2017; MaHong & SlaterTammy, 2015; S. Wang et al., 2024). Anxiety and self-doubt of students and teachers towards AI technology have been studied by Alghamdi et al. (2020) and S. Wang et al. (2024). However, when students think about their career future with respect to AI automation, this becomes a problem they face (Salloum et al., 2024). In addition, according to S. Wang et al. (2024), another similar challenge involves educators who fear integrating artificial intelligence in their teaching processes due to a lack of familiarity with AI. Negative attitudes could affect the behavioral intention towards using artificial intelligence in education (Bates et al., 2020; K. P. Gupta & Bhaskar, 2020).

Lack of AI Research on Socio-Emotional Aspects

Most studies regarding AI have been on cognitive outcomes and on the adaptive learning process, and few studies have investigated socio-emotional outcomes (Salas-Pilco et al., 2022; Trisnawati et al., 2023). The ethical issues of learners and faculty or staff reported incredible and similar attitudes towards AI, and it appeared that both students and faculty or staffs felt they lacked sufficient and reliable AI literacy and lacked enough time in the AI curriculum. While ethical issues have been deeply discussed in the field of AI in law, engineering, and social science, they have not yet been explored in the educational field. There are ethical and safety issues to be taken into account while collecting, using, and sharing data (Huang et al., 2021). There are several ethical issues connected to the delivery of personalized advice to students, data collection, data privacy, and the ownership of responsibilities and data feed algorithms that have arisen with the use of AI (Wyatt-Smith et al., 2020). Improving the governance of AI technology and its products requires a public conversation about the ethics, responsibilities, and safety of AI (Kahn & Winters, 2021).

The Integration of Bibliometric and Thematic Insights

The multimethod approach of this study allows for establishing links between the macro-level bibliometric patterns and the micro-level bibliographic themes, which cannot be drawn from either method alone. The keyword co-occurrence analysis shows that the terms 'ChatGPT' (173 times) and academic integrity terms are highly visible in the recent literature. In the systematic review, academic integrity is the most common theme of discussion, as indicated in the finding **Table 10**, this bibliometric pattern corresponds directly to that theme. When examining the alignment in time with the launch of ChatGPT in late 2022 and academic integrity debates featured in publications from 2023–2025, it is possible to make a case for this alignment being a relationship where the availability of generative AI tools has brought the scrutiny of academic integrity issues into focus. This finding is consistent with the insight provided by Eaton (2021), who found that the discourse in media and academia is preoccupied with the problem of cheating and academic dishonesty, which might overshadow other problems highlighted by us in the literature review, such as the problem of equity, deficiencies in teacher training, and appropriate pedagogy. In the same way, the bibliographic coupling of countries, **Figure 5** shows that China and the United States have a strong research output, and the thematic analysis shows that most research on automated grading systems and performance prediction comes from these countries. Conversely, Indian, Indonesia, and African countries in the sample of reviewed studies have more studies that address issues of equity and the digital divide. The geographical pattern implies that research agendas are determined by the local priorities and resource situations, with technologically advanced countries paying attention to the capability development of AI, and developing countries to the implications of access and equity.

The co-occurrence clustering in **Figure 3** also helps to clarify the thematic structure of the field. Cluster 1 (AI, curricula, integration) is related to the opportunity theme of academic support that emerged from the thematic synthesis, and Cluster 5 (ChatGPT, generative AI) is related to the prominent challenge of academic integrity that emerged from the thematic synthesis. The confluence of bibliometric and thematic results further reinforces the confidence on the dual landscape framework, where the opportunities and challenges derived from the qualitative synthesis are echoed in the quantitative patterns of words and concepts in the wider literature. Their combination of these complementary analytical tools then gives a stronger understanding than either one would be able to give alone.

Our research findings are similar yet different from existing reviews. Like Bond et al.'s (2024) meta-systematic review, we found that academic integrity and data privacy are the prevalent issues. Where Bond et al. (2024) identified ethics as the primary challenge, our meta-analysis shows that integration challenges and deficiencies in teacher training programs are equally relevant, indicating that the emphasis should now be on implementing the ethical considerations rather than on ethics itself. As opposed to Zawacki-Richter et al. (2019), who reported sparse empirical findings about the effectiveness of AI in higher education, the present literature review of 2021-2025 revealed a significant boost in empirical research, especially concerning ChatGPT. This indicates that this approach is methodologically developed although long-term studies are not common. We expand the opportunity-challenge typology of Chiu et al. (2023) by showing how opportunities can lead to challenges and vice versa, like automated grading (opportunity) can result in new integrity vulnerabilities (challenge). In previous reviews, opportunities and challenges are often presented as separate categories, without a clear focus on the interdependence. Previous reviews have not specifically theorized interdependence, but rather opportunities and challenges are presented separately.

Theoretical and Practical Contributions

The study contributes to the theoretical literature on the use of AI in higher education in several ways. First, it expands the conception of the AI in Education paradigm framework (Xu & Ouyang, 2022) to reveal that the three paradigms of AI-directed learning, AI-supported learning, and AI-empowered learning exist in wider institutional and ethical surroundings that are not completely covered by the framework. According to our results, the paradigm implementation will depend on the ethical infrastructure, AI literacy of educators, and institutional readiness, which should be added to the framework. Secondly, the dual landscape concept that emerged from this synthesis offers an analytical frame for a balanced discussion on techno-integration, beyond techno-utopian and techno-dystopian approaches. Third, this paper shows the methodological benefits of combining bibliometric and systematic review methods, offering a model for multimethod reviews in the field of educational technology in the future.

Finally, although there are systematic reviews of the literature pertaining to artificial intelligence in education (e.g., Bond et al., 2024; Chiu et al., 2023; Zawacki-Richter et al., 2019), the former usually addresses the topic within a K-12 setting, and the latter within digital learning. The review is the first multimethod integration of the field specifically for higher education that addresses the intellectual structure and the substantive findings of opportunities and challenges in higher education (2021–2025).

Practical contributions include an evidence-based typology of opportunities and challenges **Table 9** and **Table 10,** that can inform institutional AI strategy development. The finding that opportunities and challenges are often interdependent, for instance, automated assessment systems that improve efficiency may simultaneously create new integrity vulnerabilities, suggests that institutional policies should address these dimensions holistically rather than separately. Further, the gaps in the existing research (socio-emotional focus, lack of multi-disciplinary AI tools, lack of teacher professional development models) offer a focused research agenda for future research.

IMPLICATIONS

Policymakers have three priority areas for action identified by this review. To begin with, any institutional policies on AI should involve the aspects of academic integrity, data privacy, transparency of the use of AI algorithms, and equal access to AI infrastructure, as they are all interconnected. Secondly, there is a need for the training of instructors in terms of AI literacy. The training process should go beyond the mere training on the use of AI technology. Based on our findings, we recommend three strategies for educators. First, assessment tasks should be redesigned to focus on higher-order thinking, authentic problem-solving, and personal reflection approaches that will utilize the capabilities of AI and will not be as vulnerable as traditional approaches would be to AI-accelerated academic dishonesty. Second, educators need to have a critically engaged attitude towards the use of AI tools, using them where they clearly add value to learning and with pedagogical intentionality in their usage. Third, participating in an ongoing community of practice can foster confidence and competence for effective AI integration.

From a research perspective, this review highlights five areas of interest for future research: (1) Long-term studies to track the long-term impact of AI integration on learning outcomes, student engagement, and educational equity; (2) design-based research for developing and testing multidisciplinary tools for AI use in education, specifically for other school subjects, beyond STEM; (3) mixed methods research exploring the socio-emotional implications of AI integration, such as its effects on student motivation, teacher self-efficacy, and the development of ethical reasoning; (4) comparative studies on the implementation of AI across various institutional types, cultural settings, and resource levels; and (5) research on effective teacher professional development models to enhance the capacity for sustainable AI literacy and pedagogical integration.

Limitations

First, the use of English-language publications in Scopus, Web of Science, and PubMed might be biased towards research from non-English-speaking parts of the world and not cover journals that are not indexed in these databases. This may introduce bias in the geographic and thematic patterns that are identified. Second, the field of AI technology is constantly changing, and findings, especially concerning specific tools (e.g., ChatGPT) and their capabilities, may need to be updated as the technology advances and new applications are developed. Third, while we added Cohen's kappa for inter-rater reliability (see Method section), percentage agreement was used initially, which is less robust. Fourth, the bibliometric analysis used Scopus exclusively; inclusion of additional databases (e.g., Google Scholar, Dimensions) might reveal different citation patterns. Fifth, the quality appraisal using the JBI checklist, while systematic, involves subjective judgments; different appraisers might produce different classifications.

CONCLUSION

This multimethod systematic review and bibliometric analysis examined the dual landscape of artificial intelligence integration in higher education from 2021 to 2025. The study makes three central contributions. The bibliometric analysis firstly identifies the key scholars and shows that the field is rapidly maturing with the paradigm-defining work of scholars such as Jiao, Ouyang, and Zheng, whose research has laid the groundwork for AI-directed, AI-supported, and AI-empowered learning. The keyword co-occurrence results show that since the end of 2022, ChatGPT and generative AI are predominant research topics, leading to significant attention in the context of academic integrity implications. Second, the creation of a thematic synthesis of 110 high- and medium-quality studies shows that the integration of AI has significant opportunities in three academic support areas: academic integrity threats, data privacy concerns, and integration barriers, along with equity issues. Importantly, these opportunities and challenges are interdependent; a change in one will impact the other. Third, it introduces a balanced analytical framework of the dual landscape that is proposed here, which transcends the techno-utopian and techno-dystopian accounts. With regard to practice, the review provides an evidence-based typology of institutional AI strategies, priority areas for policy action, and a targeted research agenda. In an era where the landscape of AI technologies is constantly evolving, the dual landscape framework provides a stable frame of reference for shaping evidence-based policy strategies, pedagogical approaches, and future research on the integration of AI in higher education.

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Ethical statement: The current paper is a secondary analysis of peer-reviewed sources of the existing body of literature. No experiments were conducted in the course of the research, and no interaction took place between the researcher and any human or animal beings. Thus, in accordance with the guidelines of the journal under which the paper will be submitted for consideration, ethical approval was not necessary for the research since there were no violations of ethical standards (as stated in the Declaration of Helsinki).

AI statement: The authors used ChatGPT to assist with grammar checking and improving language fluency. All AI-generated suggestions were reviewed and edited by the author. We take full responsibility for the content and integrity of the published work.

Data sharing statement: The bibliometric datasets generated and analyzed during this study are available from the corresponding author upon reasonable request. The systematic review data extraction forms and coding frameworks are included as supplementary materials.

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